Quality of life is a matter of distance?
A study investigating the association between transport accessibility to healthcare and health inequalities for patients with Rheumatoid Arthritis and Osteoarthritis

---

Charlotte Elizabeth Kelly

Submitted in accordance with the requirements for the degree of Doctor of Philosophy

University of Leeds

School of Medicine

April 2019

Intellectual property and publications

The candidate confirms that the work submitted is her own, except where work which has formed part of jointly authored publications has been included. The contribution of the candidate and the other authors to this work has been explicitly indicated below. The candidate confirms that appropriate credit has been given within the thesis where reference has been made to the work of others.

Publications

Part of the work described in Chapter 2 (the systematic review) has been published as a journal paper and review protocol listed below.

Title: Are differences in travel time or distance to healthcare for adults in global north countries associated with an impact on health outcomes? A systematic Review

Reference: 2016, BMJ Open, 12 (11)

Authors: Kelly C, Hulme C, Farragher T, Clarke G.

Title: Protocol – Do differences in travel time or distance to healthcare for adults in global north countries impact on health outcomes?

Authors: Kelly C, Hulme C, Farragher T, Clarke G.

Reference: PROPSERO CRD42014015162.

The candidate confirms that she wrote the protocol, carried out the research and wrote the paper. CH reviewed 20% of the abstracts and papers and undertook 20% of the data quality assessments to confirm validity. CH, GC and TF all provided comments on drafts.

Abstract

This study explored the association between transport accessibility to healthcare facilities and health outcomes for patients in England with Arthritis. The aim was to provide evidence on the impacts on patient health from changing where patients attend hospital and a method for evaluating who would be affected under a range of scenarios. The study had three main stages:

1. Systematic review to consider the current evidence. This review focused on studies that had considered the associations between travel time/ distance and health outcomes in global north countries. Out of 108 identified studies 77% reported evidence that patients who live further from where their healthcare is provided have poorer health outcomes.
2. Exploring the association. The study used two datasets to explore the association between transport accessibility and health outcomes. These were the linked Hospital Episode Statistics and Patient Reported Outcomes Measures dataset (using West Yorkshire patient data) and the English Longitudinal Study of Ageing (using a national sample). These were used to assess whether travelling further to the hospital or the GP was associated with poorer health. The results include some evidence of a decline for those travelling the furthest, but importantly that the key association with health outcomes was ease of travel. The burden of travel to healthcare was exacerbated for individuals without access to a car, living alone and with mobility issues.
3. Assessing the impact of changes to healthcare provision. Using mapping techniques (including location-allocation methods), the study has assessed the impact on patient travel and inequalities within groups for a number of service provision scenarios. Modelling was used to predict changes in health outcomes from these changes.

These findings can help inform future planning decisions concerning where patients attend healthcare services to minimise the impact on patient travel and health inequalities.

Acknowledgements

Firstly, to my supervisors Prof Claire Hulme, Prof Graham Clarke and Dr Tracey Farragher – I thank each of you for all of the help and support that you have provided throughout my PhD. You are inspirational and are shining examples of academics that are not only sharp, tough, but also kind.

To my Patient Public Involvement Group – I thank you so much for giving up your time to talk with me and discussing the impact that travelling to hospital has on your daily lives. This research has benefited hugely from having you as part of my study.

I thank the NIHR for funding this research, which was funded through an NIHR Doctoral Research Fellowship.

I dedicate this thesis to my husband Tim and children Isaac, Joseph and Levi. I am so blessed having you all in my life.

"…My precious child, I love you and would never leave you,

Never, ever during your trials and testings.

When you saw only one set of footprints,

It was then that I carried you." (Powers, 1964)

Contents

Figures

Tables

Maps

Appendix

List of Abbreviations

A & E	Accident and Emergency
BMI	Body Mass Index
CASP	Critical Appraisal Skills Programme
CASP-19	Quality of Life Measure
CCG	Clinical Commissioning Group
CESD	Centre for Epidemiological Studies-Depression
CI	Confidence Interval
CRD	Centre for Reviews and Dissemination
DAG	Directed Acyclic Graph
DfT	Department for Transport
DMARDs	Disease- Modifying Anti-Rheumatic drugs
DNA	Did Not Attend (appointment)
ELSA	English Longitudinal Survey on Ageing
EQ-5D-3L	Descriptive system of health related quality of life
EQ-VAS	Quantitative measure of health outcome
GIS	Geographical Informational System
GP	General Practice
HES	Hospital Episode Statistics
HHS	Harris Hip Score
HOOS	Hip Disability and Osteoarthritis Score
HOS	Hip Outcome Score
HSCIC	Health and Social Care Information Centre
HRA	Health Research Authority
HRQoL	Health Related Quality of Life
IMD	Index of Multiple Deprivation
IRAS	Integrated Research Application System
ITN	MasterMap Integrated Transport Network
IRP	Independent Reconfiguration Panel
Kmph	Km per hour

KOOS	Knee disability and Osteoarthritis Outcome Score
LEFS	Lower Extremity Functional Scale
LoS	Length of Stay
MAR	Missing at Random
MCID	Minimal Clinical Important Difference
MRI	Magnetic Resonance Imaging
MSK	Musculoskeletal
MSOA	Middle Super Output Area
NatCen	Britain's largest independent social research agency
LSOA	Lower Super Output Area
NaPTAN	National Public Transport Access Nodes
NICE	National Institute for Health and Care Excellence
NHS	National Health Service
OA	Osteoarthritis
OHS	Oxford Hip Score
OKS	Oxford Knee Score
OR	Odds Ratio
OS	Ordinance Survey
PCT	Primary Care Trust
PICOS	Population, Intervention, Comparator, Outcome, Study Type
PROMS	Patient Reported Outcome Measures
PTS	Patient Transport Service
RA	Rheumatoid Arthritis
REC	Research Ethics Committee
RMSE	Root Mean Square Error
SEU	Social Exclusion Unit
SHA	Strategic Health Authority
6Mwt	Six minute Walk Test
STP	Sustainable Transformation Partnerships
THR	Total Hip Replacement
TKR	Total Knee Replacement

TUG	Timed up and go test
VIF	Variance Inflation Factor
WOMAC	Western Ontario and McMaster Universities Arthritis Index
WY	West Yorkshire

1 Chapter 1: Introduction

1.1 Introduction

This thesis was designed to investigate the potential impact on health inequalities from policies such as centralisation of healthcare services or restructuring where treatment takes place. It does this by exploring the association between transport accessibility to healthcare and differences in health for individuals through the current literature (by way of a systematic review), a case study of patients in West Yorkshire (WY) who have had a total hip replacement (THR) or total knee replacement (TKR) operation and a case study of individuals in England who have Osteoarthritis (OA) or Rheumatoid Arthritis (RA). Based on the results from the case studies and the systematic review, the thesis simulates a number of scenarios focusing on the impact of changes to where patients access healthcare and the predicted impact on health outcomes from this. This chapter provides the context and background to the research together with the key aims and objectives and summaries of the subsequent chapters.

1.2 Policy Background

Over recent years there has been a move towards the reconfiguration of healthcare services and specialised healthcare centres both in the UK and more widely (Douw et al., 2015; Hollingworth and Ness, 2012). This has been driven by a number of factors including increasing costs of providing healthcare (with budgets that have not risen to meet this), but has also allowed increased specialisation of teams to treat specific diseases that could not be replicated in every hospital (in terms of training, staff required and budget) (Luft et al., 1986; Maerki et al., 1986; Ho and Hamilton, 2000). There is evidence that having specialist teams in fewer hospitals will have a positive impact on the health outcomes of those patients treated in these specialised centres (Woo et al. (2012), Forshaw et al. (2006)). However, there are also drawbacks from increasing the distance patients travel to attend healthcare; specifically a "distance decay" association, which suggests that those who live closer to healthcare facilities have higher rates of utilisation after adjustment for need than those who live further away (Haynes, 2003; Goddard and Smith, 1998). Indeed as long ago as 1850 Jarvis proposed this distance decay effect, finding that fewer patients were admitted to a mental hospital in Massachusetts the further they lived from that hospital (Hunter and Shannon, 1985). There is also evidence that not only are utilisation rates lower, but that those attending from further afield have poorer health outcomes (Baade et al., 2011; Jones et al., 2008b). At a primary care level there is evidence that increased

distance to GP practices can have a negative impact on health outcomes (Jones et al., 1998) and studies such as Haynes and Bentham (1982) have demonstrated that the number of visits made by relatives and friends to see inpatients decreased with increasing distance from the patients' homes to the hospital. Whilst there is evidence of this "distance decay" effect both, in terms of utilisation of healthcare and health outcomes, there is less evidence on how this impacts on health inequalities. It is important to consider the impact of changing where patients attend healthcare facilities on health inequalities and where possible adjust policies to reduce these inequalities especially where they are deemed unfair.

This conflict of centralisation vs. locally provided healthcare is a growing point of debate. A recent study by Morris et al. (2014) found there were clear health benefits (increased survival) for patients from centralising stroke care in a large metropolitan area (London). It could be argued that the difference in distance between the nearest hospital to the patient and the centralised hospital attended in London is relatively small compared to other areas of the UK, especially where hospitals are more sparsely located. A number of studies have shown that there are benefits to consolidating resources into fewer hospitals leading to scale benefits from learning by doing and treating larger volumes of patients with the same illnesses (Luft et al., 1986; Maerki et al., 1986; Ho and Hamilton, 2000). These studies conclude that this consolidation increases healthcare quality and has a positive impact on patients' health and so is desirable, but also highlight that the disease context may be crucial. As the trend towards the potential restructuring of healthcare services gathers pace through initiatives such as the Sustainable Transformation Partnerships (STPs) in England, there are likely to be differences in the trade-offs for patients between travelling further and improvements in health. STPs are NHS and local authority partnerships that work together to provide a more holistic approach to patient care (NHS England, 2017). Each region in England has been required to develop plans to show how they are going to provide healthcare in the future. A number of STPS include plans to shut certain hospitals, downgrade others and restructure how services are provided (NHS England, 2017). Following the growing trend of centralisation there is also a growing call to reverse this. Simon Stevens (Chief Executive of the NHS, UK) stated that "*patients are being robbed of dignity and compassion because of a lack of local care"* (Guardian, 2014). Having to travel further and the impact this has on patients' health requires further investigation. This thesis will look at the potential impacts on health inequalities from such policies.

1.3 Health Inequalities

Health inequalities are *"differences, variations, and disparities in the health achievements of individuals and groups" ((Kawachi et al., 2002) p647).* Whilst some differences in individuals health are to be expected in society (e.g. older people are more likely to be in poorer health than younger people) the key concern is for *"the absence of avoidable, unfair or remediable differences among groups of people whether those groups are defined socially, economically, demographically or geographically or by other means of stratification. "Health equity" or "equity in health" implies that ideally everyone should have a fair opportunity to attain their full health potential and that no one should be disadvantages from achieving this potential" (WHO, 2019).* The NHS was launched in 1948 and was the first healthcare system in Western society to provide free healthcare to the whole population, with one of the founding principles to improve health equity. The NHS was designed to be "*universal, equitable, comprehensive, high quality, free at point of delivery and centrally funded"* Delamothe (2008), p 1216). If access to healthcare does differ for those in equal need this does not satisfy the equitable criteria and could lead to health inequalities. The Acheson report - an independent enquiry into health inequalities in the UK, recommended that *"all policies likely to have an direct or indirect impact on health should be evaluated in terms of their impact on health inequalities, and formulated in such a way that by favouring the less well-off they will, wherever possible, reduce such inequalities"* ((Acheson, 1998) p *75*). If changes to where patients access healthcare are expected to impact on health in any way then this provides ample justification for researching this issue. The Marmot Review of 2010 goes further and states that *"health inequalities that are preventable by reasonable measures_are unfair. Putting them right is a matter of social justice"* (Marmot, 2010). Finding solutions to minimise health inequalities is therefore desirable.

Health inequalities can be observed between countries. For example, residents of Angola in Africa had a life expectancy at birth of 61.5 compared to the UK of 80.95 and Australia of 82.5 in 2016 (World Bank, 2019). Heath inequalities can be observed within countries. For example, in the UK males living in Kensington and Cheslsea had the highest life expectancy at birth at 83.4 years compared to males living in Glasgow who had the lowest life expectancy at birth of 73.4 years (ONS, 2018c). Health inequalities can also be observed across cities. For example, research from the London health observatory identified that starting from individuals living in Westminster in London (see Figure 1) and travelling east that each tube stop (from Westminster tube station) represented nearly one year of life expectancy lost (London Health Observatory, 2014). By the time you got to those individuals living in Canning Town the male life expectancy

was on average 6.1 years less than those living in nearby Westminster with slightly lower differences for females of 3.6 years.

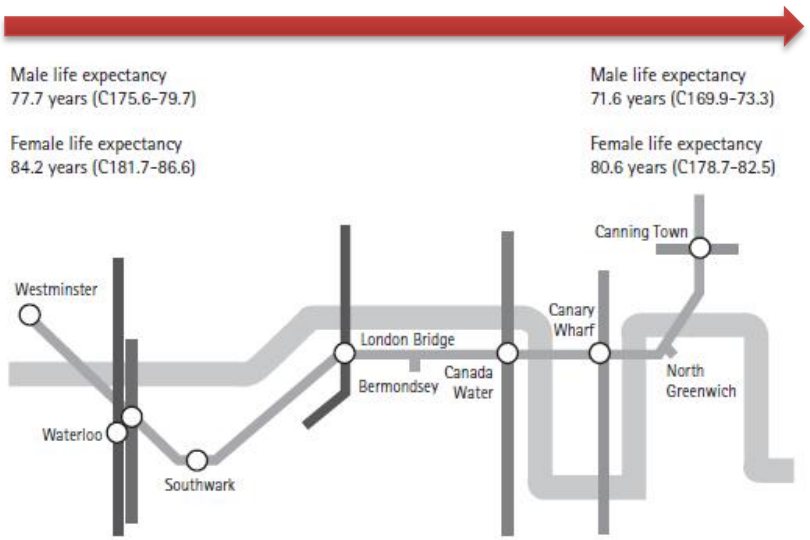


Figure 1: Life expectancy within London a tube map. source: (London Health Observatory, 2014)

A wide range of differing and interconnecting factors that can influence an individual's health have been identified in the literature. These factors are commonly characterized into an individual's genetics (e.g. age), the economy and environment that they live in (e.g. there local community) and the choices that they make (e.g. lifestyle – including smoking), as shown by Figure 2. This includes where their live, their levels of interactions with other people, where they work, shop and the physical environment that they have access to. Transport accessibility to healthcare (the focus of this thesis) plays a key role in this wheel of health and wellbeing. But there are of course many others some of which are now described.

One of the key areas identified in the literature linked with differences in health among the population are levels of deprivation. This is commonly represented in the UK using the Index of Multiple Deprivation (IMD), which is relative deprivation at the lower level super output area (LSOA) in England (Department for Communities and Local Government, 2011). It is a composite index combining data from seven domains: Income Deprivation, Employment Deprivation, Health Deprivation and Disability, Education, Skills and Training Deprivation, Barriers to Housing and Services, Crime, Living Environment Deprivation, so recognising that deprivation is a multifaceted construct. It does not measure an individual's deprivation, but the relative deprivation for the location (LSOA) that they live. A range of studies have considered the impacts of area deprivation on population health. ONS (2018c) reported that boys born in the

least deprived areas in 2016 would be expected to live 9.3 years longer than those in the most deprived areas and the gap for girls was 7.4 years. Studies in the UK have reported that patients with OA who need a hip or knee replacement in the most deprived groups are less likely than those in the least deprived groups to have a joint replacement (Judge et al., 2010).

Figure 2: Determinants of health and wellbeing (Source: Barton and Grant (2006))

The social networks- the people and community surrounding an individual (their social capital) have been found to contribute to the health of individuals. Putnam (2000) summarized research from around the world identifying that *"people who are socially disconnected are between two and five times more likely to die from all causes, compared with matched individuals who have close ties with family, friends, and the community"* (p 327). Other research has shown that living alone is associated with differences in a range of health outcomes including delays in hospital admissions, increased length of stay in hospital and patients being less likely to be discharged to their own home (Agosti et al., 2018; Fleischman et al., 2018), more frequent readmissions and worse health outcomes (Edwards et al., 2018). Theiss et al. (2011) found that patients undergoing joint replacements that had strong social support had "*shorter hospital stays, are*

more likely to be discharged home, to meet ambulation and transfer-out-of-bed targets, and to score hospital quality of care higher, and are more confident and ready to go home on discharge" (p357). It might be expected that having greater social networks and not living alone would improve a patient's ability to travel to healthcare when needed.

Another key group showing differences in health is gender. This was shown clearly in Figure 1 where there were differences in the life expectancy between males and females. The factors that affect health for men and women differ, for example, conditions such as polycystic ovary syndrome affect only women, others such as OA are more prevalent in women at a younger age than men and treatments differ. WHO (2001) identified that there was a need to focus differently on men and women, due "to their biological differences and their gender roles, have different needs, obstacles and opportunities" (p2). A number of studies have reported worse outcomes for women with Rheumatoid Arthritis (RA) compared to men with RA, in particular with women having more severe disease than men and lower remission rates (Symmons, 2002; Forslind et al., 2007). Similarly there are studies that indicate that women with Osteoarthritis (OA) report worse knee pain and hip pain and reduced function than men with OA (Tonelli et al., 2011). Studies have shown that OA displays differently in men and women, particularly in certain parts of the joints. For example, Hanna et al. (2009) found that women have increased rates of cartilage loss and more cartilage defects than men in their study

It is widely reported that health and physical function declines with age. Ageing can be described as the "progressive changes in the tissues or organs of the body, leading to decline in function and death" (p *836*). It is affected by the full spectrum of factors portrayed in Figure 2. Grundy and Holt (2000) identified that adults who had experienced more difficult lives (e.g. Death of a child, long periods in unemployment), were more likely to report being in poorer health at an older age than matched equivalents. Changes over time lead to increases in problems such as falls, as people age, but contributing are factors such as life transitions, where changes such as retiring from work can influence health (Grundy and Holt, 2000).

Research has shown a high rate of prevalence of comorbidities (one or more diseases alongside OA or RA) for patients with OA (Kadam et al., 2004) and RA (Dougados, 2016) . Kadam et al. (2004) matched by sex and age 11,375 patients over the age of 50 who had attended a GP in England and Wales for OA with 11,375 without OA and found that there were statistically significant associations with having OA and comorbidities including, upper limb sprain, synovial and tendon disorders, obesity, gastritis, phlebitis, diaphragmatic hernia, ischaemic heart disease and intestinal diverticula. A review of studies focusing on comorbidities in patients with RA by

Dougados (2016) found that studies had identified lung cancer, lymphoma, atherosclerosis-related cardiovascular diseases, infections, osteoporosis, gastrointestinal disorders and depression, as comorbidities at higher rates than would be expected in the general population.

A number of studies have focused on whether health differs by ethnic group. It is documented in the UK that individuals from non-white groups have poorer health than people from white groups, with individuals living in the UK originally from Bangladeshi having the poorest health (Nazroo, 2014; Evandrou et al., 2016). Nazroo (2014) argues that the key reasons for differences in health by ethnic group include; genetic differences, migration effects, cultural differences, poorer access to quality healthcare and socio-economic inequalities including experiences of racism and discrimination. Smith et al. (2017) found that ethnic minorities were less likely to receive a Total Hip Replacement (THR) or Total Knee Replacement (TKR) than their white counterparts and also identified that patients with OA having a THR or TKR from ethnic minority groups were younger and from more deprived areas.

Lifestyle factors such as smoking, physical activity, diet and alcohol use have been identified in the literature as contributing to differences in individual's health. (WHO, 2008) reported that "*Up to 80% of heart disease, stroke, and type 2 diabetes and over a third of cancers could be prevented by eliminating shared risk factors, mainly tobacco use, unhealthy diet, physical inactivity and the harmful use of alcohol" (p5).* Whilst the numbers of people smoking and inhaling secondary smoke in recent years has declined (in part due to the UK smoking ban in 2007, where it banned smoking in enclosed spaces) there are still an estimated 7.4 million people over the age of 18 smoking in the UK (ONS, 2018b). The UK has seen a steady increase in the number of admissions attributable to alcohol. (NHS Digital, 2018a) calculated that there were 337,000 admissions where the hospital admission could be directly attributable to alcohol in 2016/17, which was 17% higher than in 2006/07. In terms of physical activity levels 66% of men and 58% of women were found in 2016 to have met the expected aerobic activity level, which is "greater than 150mins of moderate activity or 75 mins of vigorous activity per week or an equivalent combination of both in bouts of 10 minutes or more"((NHS Digital, 2018d) (p1), which means that over 34% of men and 42% of women are not achieving this level. NHS Digital (2018d) also report that there was an estimated 617,000 admissions to hospital where obesity was considered a factor in 2016/17 a rise of 18% on the 2105/16 data. The negative lifestyle factors that the WHO reported in 2008 are not going away and are in the above cases getting worse contributing to the health inequalities experienced in society.

The World Health Organisation defines health as "a state of complete physical, mental and social well-being, and not merely the absence of disease". ((WHO, 1946) p1). A realisation that to

measure an individual's health is not limited to being free from disease, but also includes quality of life and social wellbeing. The first stumbling block then is how to accurately measure this definition of health in the population, so going beyond purely the categorisation of having or not having an International Classification of Diseases (ICD10) diagnosis code for a particular disease (e.g. M16 = Osteoarthritis of the hip) (WHO, 2016). Most commonly in the literature the health of the population is measured using indicators such as morbidity, mortality rate and life expectancy, which can easily be calculated and mapped overtime using national datasets. For example, the life expectancy at birth for men and women living in London in Figure 1. In order to operationalise a more holistic measure of the health of the population (not just an estimate of how long a person will live or whether they have a disease) in the context of the WHO definition a number of instruments have been developed to measure health in a variety of contexts. One of the most commonly used to measure health in the context of health economics is the EQ-5D, which was developed as a standardized measure of Health Related Quality of L ife (HRQoL) by The EuroQol Group (1990). The EQ-5D comprises of five domains; mobility, self-care, usual activities, pain/discomfort and anxiety/ depression. For the EQ-5D-3L, each domain has three possible responses (no problems/ some problems/ severe problems) and from the answers an index value of HRQoL can be generated, which could be used to assess someone level of health, but also changes in HRQoL over time (e.g. before and after operations/ procedures). Whilst the EQ-5D was designed as a generic health measure (to be applied across a range of diseases) other measures have been developed that are more context specific. For example, the Oxford Hip score (OHS) was developed to assess the level of disability in patients undergoing THR (Dawson et al., 1996) and the Centre for Epidemiologic Studies Depression scale (CES_D) developed to assess the levels of depression in the general population (Radloff, 1977). These measures are discussed in more detail in Chapters 3 and 4.

If access to healthcare does differ for those in equal need this does not satisfy the equitable criteria. Whilst there are many potential determinants of health and health inequalities understanding the impact that the journey to and from healthcare has on patient outcomes is critical. For this thesis I am focused on exploring whether differences in transport accessibility to healthcare are associated with inequalities in health, answering questions such as – Is unequal transport accessibility to healthcare associated with differences in health? Importantly recognising that in doing this there are multiple possible determinants of health, as discussed above that need to be considered.

1.4 Transport Accessibility

The role that transport plays in the health of the population was highlighted by Acheson who stated that a *"lack of transport may damage health by denying access to people, goods and services...".(Acheson (1998):* p55). Exploring whether transport accessibility to healthcare is associated with health inequalities in the population addresses one specific and potentially important linkage in this field. Accessibility has been conceptualised in a number of ways in the literature over time. Hansen (1959b) described accessibility as "*a measurement of the spatial distribution of activities about a point, adjusted for the ability and the desire of people or firms to overcome the spatial separation* "(p73). Critically Hanson identified that accessibility was not purely a distance calculation and recognised that different individuals have differing abilities and willingness to travel to get to key goods and services. More recently this definition has been simplified into "people's ability to reach desired goods, services and activities" (Litman, 2011) and in the case of this thesis patients ability to reach healthcare facilities and services. Unpicking some of the reasons why patients might find accessing healthcare facilities more difficult or impossible has been considered by a number of authors. The Social Exclusion Unit (SEU) (2003) report - Making the Connections defined transport accessibility through the following statement "*Can people get to key services at reasonable cost, in reasonable time and with reasonable ease?" (p6).* Or to put it another way:

- Does transport exist between the people and the service?
- Do people know about the transport, trust its reliability and feel safe using it?
- Are people physically and financially able to access transport? And
- Are the services and activities within a reasonable distance?

There are a number of modes of transport that patients can use to travel to healthcare services in the UK – including, but not limited to car, taxi public transport, walking/cycling, community transport and the NHS Patient Transport Services (PTS). Whilst it is most commonly reported that people travel to healthcare using a private vehicle, we know that, for example, in the UK 26% of households do not own a car, and that this percentage is higher for older households and for those with limiting long term illnesses (ONS, 2016a). For some local authorities the proportion is as high as 40% (ONS, 2016b). The SEU (2003) reported that 31% of people without a car have difficulty travelling to their local hospital, compared to 17% of people with a car. In addition 1.4 million individuals had missed/ turned down or chosen not to seek medical help over a year because of transport problems. The data illustrates that having a car does not preclude individuals from having issues with transport accessibility to healthcare, but as

described by the Health Development Agency (HAD) *"inadequate public transport is by far the most frequently mentioned transport problem identified by people who have difficulty getting to local services. Other access issues include the location of NHS sites and car parking facilities, limited access to specialist transport services for those with social needs and under-resourced community transport services"* HDA (2004) (p2).

The most common method used to measure transport accessibility to healthcare facilities is by calculating the travel times and distances that patients would have to travel to get to the healthcare facilities. Either to the nearest available facility or the actual facility attended. A growing number of studies have determined transport accessibility levels to healthcare using Geographical Information Systems (GIS) techniques, by mapping car and public transport travel times and distances to healthcare facilities. These can be broadly split into revealed accessibility and potential accessibility methods, (Khan, 1992). Revealed accessibility refers to methods that utilise data from actual healthcare trips; for example the drive time or straight-line distance between a patient's home address and the hospital they attended (Jackson et al., 2013; DeNino et al., 2010). Potential accessibility refers to methods that look at the potential for accessing healthcare facilities in a particular area, for example, using gravity models (Hansen, 1959a) and specialised gravity models, where 2 step flotation catchments areas method have been used (Lou and Wang, 2003; McGrail and Humphreys, 2009).

Local authorities in England have typically focused on the percentage of the population that can get to a specific local hospital by bus within 30 and 60 minutes in their Local transport plans, with the aim of improving this percentage (e.g. West Midlands (2006)). One of the key issues with this is that the hospital selected might not be the hospital where all patients are treated, either because it lacks the specialism they require, or because they or their GP have not chosen it for other reasons. The National Travel Survey (NTS) reports annually on the percentage of the population that could access their nearest GP and hospital within a specified time by bus or walking. In 2016 92% of individuals could access a GP in <15 minutes and 11% the nearest hospital by bus or walking in <15 minutes. Whilst all individuals could get to their nearest GP in under 60 minutes, 5% would have travel times >60 mins to the nearest hospital (DfT, 2017). The key issues with this measure is that it assumes that individuals attend their nearest healthcare facility, that individuals can walk at a speed of at least 4.8kmph and can walk a distance up to 800 metres to get to the bus stop. This may be very difficult for some groups in society, who are likely to make up a larger proportion of those attending health services. Equal access for equal need in the NHS maybe less achievable if the transport system does not allow equal transport accessibility.

In order to formalise this multifaceted concept of accessibility to healthcare facilities (multi-modal and varying in quality and affordability), the thesis turned to a utility based approach using the concept commonly used in economics of Generalised Cost (GC), which is very widely used in transport economics (Small and Verhoef, 2007). GC is the sum of the monetary and non-monetary costs of travelling from A to B. The monetary costs include out-of-pocket expenses such as bus fare, taxi fare, fuel costs and parking costs. The non-monetary costs of the journey comprise of the travel times (and the value to the patient of this time), and other aspects of the journey, such as the level of comfort or pain whilst travelling and feelings of safety and security, which are included as other sources of disutility. These key concepts are represented by equation 1 and map onto the three key areas identified by SEU (2003):

$$GC = C + VT + D \qquad \textit{Equation 1}$$

where:

- *GC = generalised cost*
- *C = Out-of-pocket costs*
- *vT = value of time, v, multiplied by the journey time T*
- *D = 'other sources of disutility'*

An individual's level of transport accessibility A, can be derived from the GC of a journey, and the relationship is an inverse one, as shown in *Figure 3*, which is represented as a deterrence function. At GC*** a journey to healthcare facilities will be rendered impossible (the GC to the individual is too high), so there is zero transport accessibility. Possible reasons for this could be that there is no viable transport option to get them to the appointment, or the pain whilst travelling is so high they can't make the journey, or their value of time is so high for when there are available GP appointment (e.g. they are at work), that they don't seek or attend an appointment. As the GC reduces the transport accessibility improves, as can be seen moving from GC*** to GC* results in an increased transport accessibility at A*. At the point at which the GC is zero there is no further improvement possible to the individual transport accessibility to the healthcare facility. Accessibility to healthcare is not infinite at this point, because even home visits have scheduling and time costs and telemedicine has time costs, so the curve intersects the axis at this point.

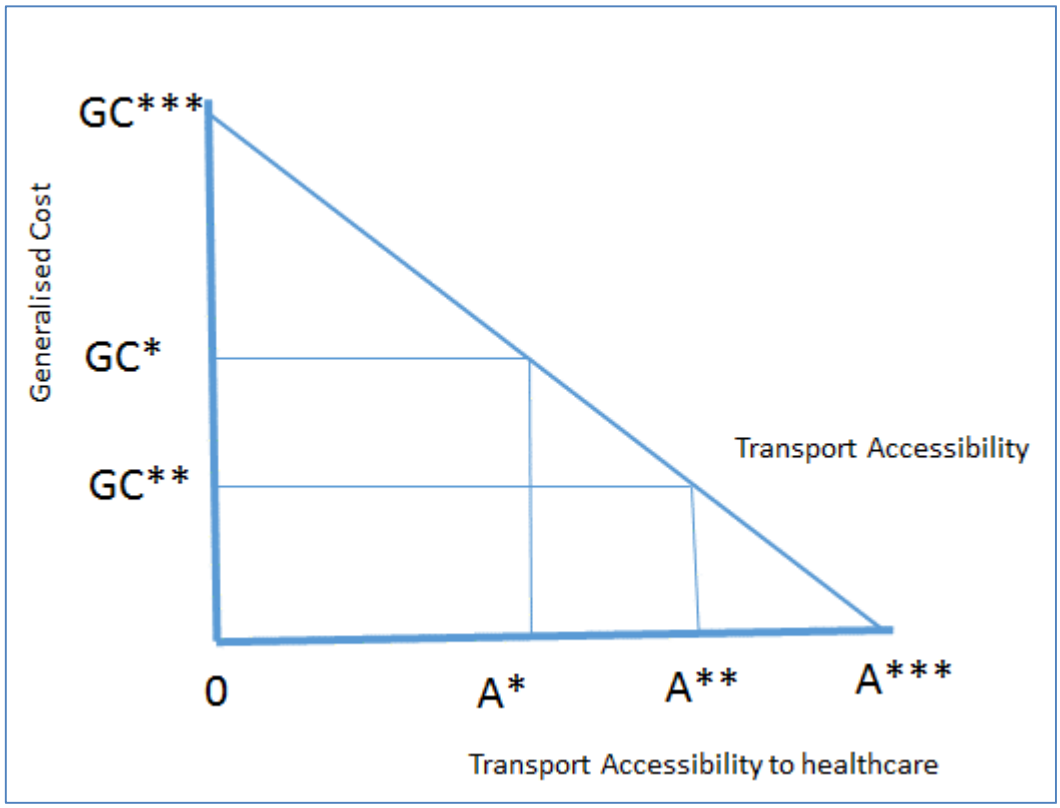


Figure 3: Measuring the impact of GC on a patients transport accessibility to healthcare

The focus of this thesis is whether policies changing where patients access healthcare, are associated with inequalities in health outcomes. What impact does this have on their GC and so association with transport accessibility and as a result the association with health outcomes? It is likely that within the patient population there are many different responses to changes in the GC of a journey to healthcare facilities. As different patients will have different weights for the components of the GC function and differing values.

To explain, there are a number of possible responses. One possibility is that for a policy such as centralisation, as GC increases (e.g. increases in travel time, or cost of travel or other disutility') transport accessibility does not change at all or reduces by a smaller proportion than the increase in GC. Under this scenario transport accessibility is said to be inelastic. The second extreme is as the percentage of GC increases transport accessibility is reduced by a larger percentage are transport accessibility is said to be elastic. These second group of patients are less likely to be able to cope with changes in the GC and as a result their transport accessibility to healthcare will fall. In the most extreme cases of an increase in GC this results in them not being able to make the journey. There are many different responses to changes in the GC of a journey to healthcare facilities.

Whilst the focus of the thesis is on transport accessibility there are other factors that can influence the level of healthcare offered to the patient. Similar affects to those identified for transport accessibility can be identified where services are not available for particular groups in the population. It is well documented in the literature and media that there are differences in provision of health care around the UK. For example, differing requirements or criteria which patient must meet for operations or labelling operations as 'procedures of limited value' (Harrogate and Rural District CCG, 2014). These are often referred to as the 'postcode lottery', as patients living in different areas have differing levels of access to the same treatment. In addition the quality of the services provided to patients might differ. For example the quality of the hospital might differ and the costs to different groups of patients may also vary. Whilst in the UK NHS healthcare is provided free at point of use, it is possible to select to pay privately and be treated more quickly for operations such as THR and TKR, so there may be difference in the cost that individuals pay for the same treatment.

It is important to understand the potential impact to patients of both how they currently access healthcare services and the impact transport has on this and how this might change under different reconfiguration scenarios. Whilst it is not possible to put a healthcare facility in all areas to minimise all patients' journeys (make all journeys equal) it is likely that some options (locations) will provide patients with a better service and minimise the impact on inequalities.

1.5 The Patient Group: Individuals with Osteoarthritis and Rheumatoid Arthritis

To explore the policy of restructuring healthcare services this thesis has focused on patients with musculoskeletal (MSK) diseases, specifically of Osteoarthritis (OA) and/or Rheumatoid Arthritis (RA). Over 8.5 million of the population are estimated to have OA and around 400,000 RA (NICE, 2014a; NICE, 2015b), the majority are over the age of 50 years old. It is estimated that the NHS spent £5.34 billion on MSK diseases in 2012/13, which was the 4th highest area after mental health disorders, circulation problems and cancers/tumours (Arthritis Care, 2012). The UK population at pensionable age is expected to increase from 12.4 million in 2016 to 16.3 million in 2041 and therefore treatment for arthritis is likely to form an increasing proportion of future NHS budgets (ONS, 2017). Research has shown that individuals with RA have worse health than those with OA and those with OA have worse health than the general population (Dominick et al. (2004)). Dominick et al. (2004) reported that compared to individuals without *arthritis "older adults with OA and RA reported poorer general health, physical health, mental health, and sleep as well as more activity limitations and pain"* (p5) and that individuals with RA reported lower Health Related Quality of Life (HRQoL) scores than those with OA. OA

and RA are treated in different ways and are associated with different health outcomes and demands on the health service.

1.5.1 Osteoarthritis

OA is the most common form of chronic arthritis. It is a chronic progressive MSK disorder characterised by joint damage, affecting cartilage and causing the growth of new bone in joints. It affects mainly the knee, neck, hip, hand, and spine, leading to painful rubbing of bone on bone in joints. Guidance for the diagnosis and care of OA in England is provided by NICE (2014a). The current care management pathway for OA is shown in Figure 4. It shows a number of stages including self-management and information about how to lose weight, with a focus on links to primary care before the patient would need to attend a hospital for further treatment (e.g. for replacement of a joint). The guidance states that before referring a person for joint surgery they must have been offered at least the core non-surgical treatments first. The emphasis is on the majority of treatment management at a primary care level including an annual review.

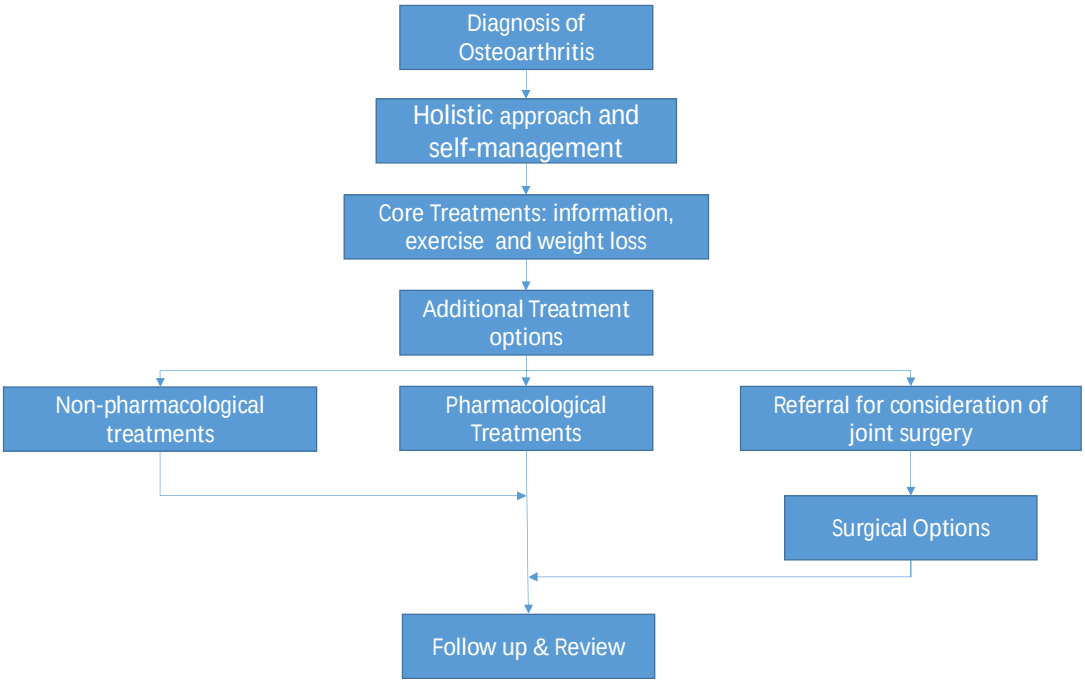


Figure 4: Management of Osteoarthritis (Adapted from (NICE, 2014a))

There are two main approaches used to diagnosis OA, these are a clinical diagnosis based on the symptoms that the patient presents with and radiographic diagnosis (and also can be used together). The first, considers the symptoms that the patient is experiencing. For example the NICE guidelines state that a person can be diagnosed at a primary care level with OA without further investigation if:

- "*they are over the age of 45, and*
- *have activity related joint pain and*
- *have either no morning joint related stiffness or morning stiffness that lasts no longer than 30 minutes"* (NICE (2014a) p1)

The second uses images, more commonly x-rays, but also Magnetic Resonance Imaging (MRI) scans or ultrasound scans that look directly at the joint to diagnose OA. These images are used to evaluate changes in the bone, osteophyte formation (lumpy bone that forms on or next to the affected joints) and joint space narrowing, as shown in the centre of the diagram in Figure 5, which can result in the bones rubbing together.

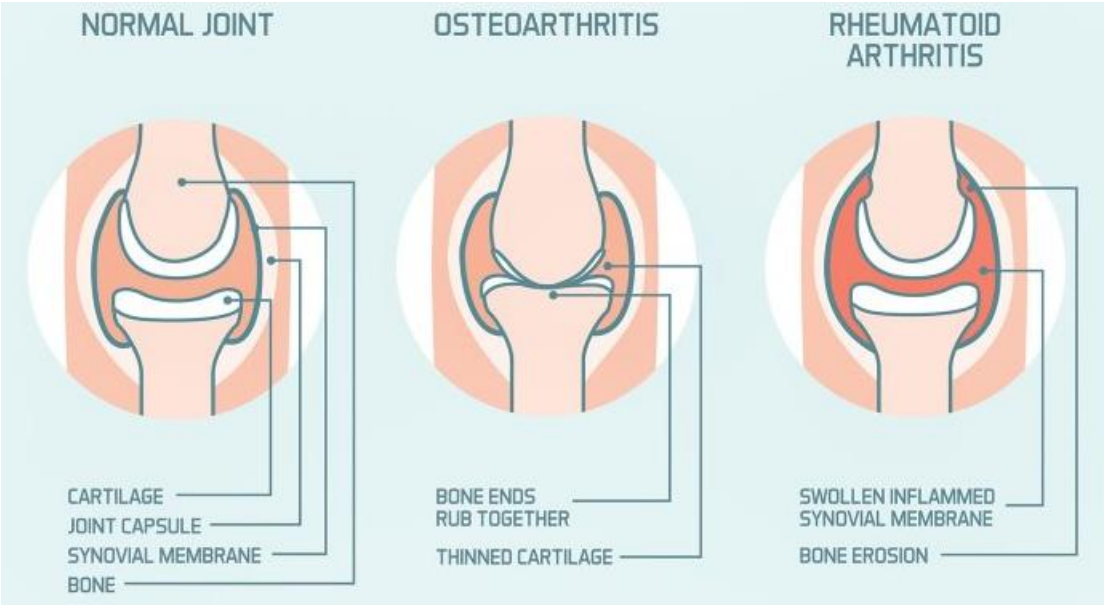


Figure 5: Graphical depiction of a normal joint, a joint with OA and a joint with RA Source: (iStock, 2019)

Research has shown that evidence gathered from using radiographic images to diagnose OA does not always align with the evidence of the symptoms reported by the patient. For example, Parsons et al. (2015) compared whether the radiographic, clinical and self - reported diagnoses of knee OA for ~400 men and women correlated and found that 58% of those with a radiographic OA diagnosis of the knee did not have either a self-reported diagnosis of OA or symptomatic diagnosis of OA. Kim et al. (2015) reported a discordance between the two methods of diagnosis for hip OA with 9.1% of patients with a clinical diagnosis also having evidence of radiographic hip OA and 23.8% of those with a radiographic diagnosis reporting painful hips. Not all individuals who have a radiographic diagnosis of OA have the relevant symptoms for the

symptomatic diagnosis and not all patients who have a symptomatic diagnosis have radiographic evidence of OA. In England NICE (2015a) argue against using radiographic images where the clinical diagnosis criteria, as described above have been satisfied, stating that *"minimal changes* [in the joint] *can be associated with substantial pain, or modest structural changes to joints can occur with minimal accompanying symptoms"* (p50). Other studies have argued that radiographic evidence is not enough on its own as, whilst a patient might exhibit radiographic evidence, which indicates changes to the structure, the symptoms of OA are exacerbated by other aspects including comorbidities, muscle strength, mood and obesity (Issa and Sharma, 2006).

Reviews focusing on the epidemiology of OA have identified a range of risk factors where individuals are more likely to have a diagnosis of OA. The literature splits the risk factors into person level and joint level characteristics. Person level risk factors include Age, gender, obesity, genetics and diet, whilst joint level risk factors include injury, joint loading and deformity of the joint (Palazzo et al., 2016; Allen and Golightly, 2015; Glyn-Jones et al., 2015; Issa and Sharma, 2006; Vina and kwoh, 2018). The loss of function and pain from having OA can have major impacts on quality of life affecting both the physical and mental health of the individuals. Research has shown associations between having OA and increased risk of falls (Prieto-Alhambra et al., 2013; Hoops et al., 2012), reduced ability to perform daily tasks at home (McIntyre et al., 2014) and at work (Harris and Coggon, 2015), issues with walking and climbing stairs (Felson et al., 2000) and evidence of higher rates of suicidal thoughts than the general population (Tektonidou et al., 2011).

1.5.2 Rheumatoid Arthritis

RA is a chronic progressive auto-immune disease, which causes inflammation in the joints, leading them to become swollen, tender and warm, while stiffness limits joint movement. Rheumatoid Arthritis is an incurable disease that affects approximately 500,000 individuals in England (Symmons, 2002). The RA joint is shown the right hand side of Figure 5 shown with a swollen inflamed synovial membrane and bone erosion. Whilst incurable, patients can go into remission for periods of time. Patients with RA usually present with symmetrical inflammation of the small joints, most commonly the metacarpophalangeal, proximal interphalangeal and the metatarsophalangeal joints. Key symptoms include joint pain, early morning stiffness and swelling round joints. Patients are referred to specialists quickly, as research has shown that early treatment within 3 months of onset can reduce disability and long term damage (Lard et

al., 2001). The current NICE guidelines for diagnosis of RA in England state that patients with suspected persistent synovitis of undetermined cause should be referred for specialist opinion if any of the following apply:

- *The small joints of the hands or feet are affected*
- *More than one joint is affected*
- *There has been a delay of three months or longer between onset of symptoms and seeking advice.*

In order to make a diagnosis of RA there is then a suite of tests added to the criteria above. Patients can be tested for rheumatoid factor in their blood. This is an autoantibody found in around half of patients with RA, but can also be found in patients without RA such as those with infections (NHS, 2019b). Studies have found that smoking status and age increases the prevalence of rheumatoid factor in the general population (JÓNsson et al., 1998; van Schaardenburg et al., 1993) without them having RA. Testing for rheumatoid factor is not 100% accurate in diagnosing RA, as it does not identify all individuals with RA and does identify some without. The next test measures a different antibody in the individual's blood an anti–cyclic citrullinated peptide (anti-CCP), which is predominantly found in individuals with RA. This test has much better specificity (96%), so rules out more of those without RA, but, as the review of studies by Braschi et al. (2016) reported that it is only present in 25% – 50% of patients before or at diagnosis, so a negative result does not rule out a positive diagnosis of RA. The final method that is used to enable a diagnosis is to carry out an x-ray (and or ultrasound or Magnetic Resonance Imaging (MRI)) on the hands and feet to look for damage to the bones.

The diagnosis and care guidelines for RA in the NHS in England are described in NICE (2015b). The management pathway for RA patients in England is shown in Figure 6. Like the management of OA there is guidance on diets, but the focus lies on hospital attendance for treatment and diagnosis. RA can 'flare up' at times and the emphasis is on patients having a named person at the hospital to contact in these times to manage their care. The main treatment is through drugs called disease-modifying anti-rheumatic drugs (DMARDs), although surgery is offered to patients to improve joint function, reduce pain and to prevent deformity. The guidance states that patients with recent onset of the disease should be monitored monthly and that all patients with RA should have an annual review and access to a specialist at the hospital. A number of studies have reported increased prevalence of certain comorbidities including cardiovascular disease, infections and malignancy in those with RA (Dougados et al., 2013 ; Avina-Zubieta et al., 2008; Uresson and Matteson, 2013).

These comorbidities also increase the likelihood of the need to attend healthcare more regularly. Unlike OA, which can be diagnosed by the GP, RA requires referral to a specialist.

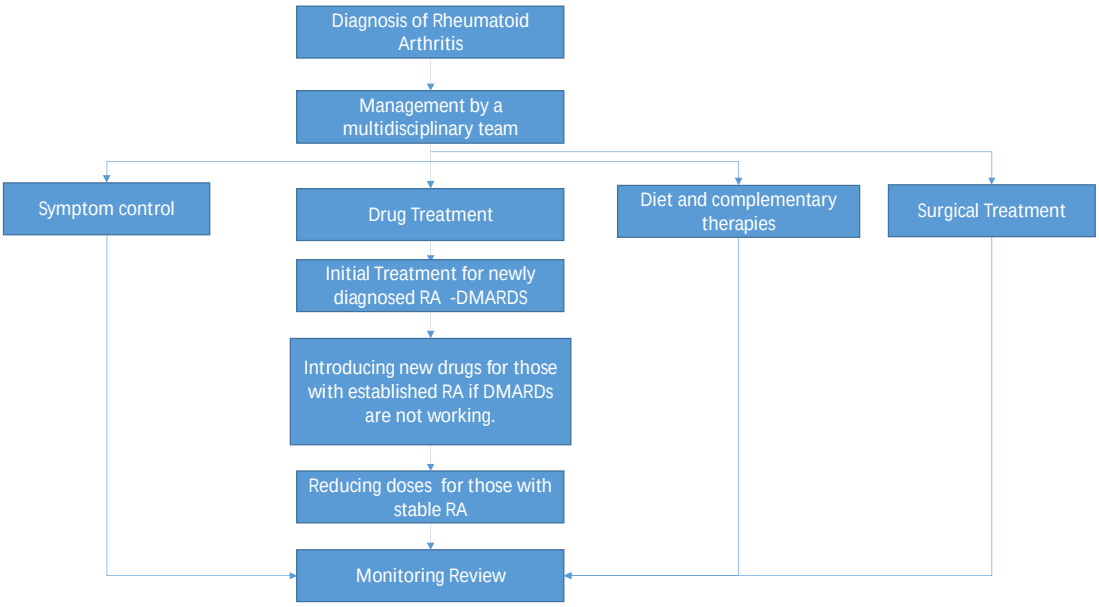


Figure 6: Management of Rheumatoid Arthritis (adapted from NICE (2015b))

Studies focusing on the epidemiology of RA have identified a range of risk factors where individuals are more likely to have a diagnosis of RA (Allen et al., 2018). Although the mechanism of developing RA is unclear the literature has investigated a number of genetic, environmental and personal /lifestyle factors associated with developing RA and its severity (Symmons, 2003; Alamanos and Drosos, 2005). Studies have shown that women are more likely to get RA than men at a ratio of 3: 1, with a higher ratio of women to men diagnosed at an earlier age (Alamanos and Drosos, 2005). Research has shown that those patients diagnosed with RA before the age of 60 tend to be more likely to enter spontaneous remission, whereas older-onset patients have more active disease and are more disabled when help is sought (Symmons, 2003). Socio economic factors have shown no evidence for being a predictor of risk of developing RA, but there is some evidence that socio economic status is associated with different prognosis of the disease, with those individuals in lower socio economics groups having worse outcomes following treatment (Symmons, 2003). Although it is not clear how this currently manifests itself. A large number of studies have focused on the association between smoking as a risk factor for the development of RA (Wilson and Goldsmith, 1999). Against this there is some evidence that smoking may have a protective effect in reducing joint inflammation in the early stages of RA and so limiting bone deterioration (Harrison, 2002). A number of studies have sought to focus on the protective effects of diet (in terms of fish, olive oil and cooked vegetables)

on development of RA. Sköldstam et al. (2003) reported on the protective effects of having a Mediterranean diet on development of RA, which resulted in *"a reduction in inflammatory activity, increase in physical function and improved vitability"* (p208). Different ethnic groups in society have been found to have different prevalence rates of RA with a higher prevalence rate in North America and North Europe than in other areas of the world (Alamanos and Drosos, 2005).

As with OA the loss of function and pain from having RA can have a major impact on quality of life affecting both the physical and mental health of the individuals. Studies have shown that patients with RA have a higher prevalence of depression and anxiety than the general population (Margaretten et al., 2011). There are associations with not being able to work, with the disability caused by onset of RA in some cases preventing individuals from carrying on working (Young et al., 2002). Patients with RA are more likely to report having lower quality of life, with increased pain, disease and reduced physical function and level of independence (Malm et al., 2017) Tengstrand et al. (2008) questioned 1000 RA patients in Sweden and found that 80% had current foot problems and 71% found walking difficult. A range of potential impacts on quality of life have therefore been identified.

1.6 Patient Public Involvement Group (PPI)

At the start of the study a PPI group was set up that included five patients who had had experience of RA, OA or both. This group was recruited through the Leeds Biomedical Research Centre. This involved advertising the roles and setting out the expectations of being part of the group. The objective of this group was to ensure that the study focused on patient need. The group met six times during the study and were a dedicated group who contributed their experiences of travelling to healthcare for appointments and treatment and was a great benefit to the study. One of the original group members also read and commented on my original proposal. Key aspects brought out by the PPI group are discussed where relevant in this thesis.

1.7 Aim and Objectives

The aim of the thesis is:

To investigate the association between transport accessibility to healthcare and health inequalities for individuals with rheumatoid arthritis and osteoarthritis

In order to achieve this aim the following objectives have been determined:

Objective 1: To undertake a systematic review to provide evidence concerning the association between transport accessibility to healthcare and health outcomes.

Objective 2: To explore and document the healthcare and transport accessibility needs of patients with osteoarthritis and rheumatoid arthritis.

Objective 3: Develop statistical models to examine the associations between transport accessibility to healthcare and inequalities in health for individuals diagnosed with RA and OA. For two case studies:

- Case Study 1: West Yorkshire. Using the linked Hospital Episode Statistics – Patient Reported Outcome Measures (HES-PROMS) dataset
- Case Study 2: England. Using the English Longitudinal Study on Ageing (ELSA) dataset

Objective 4: To employ the results of the systematic review and statistical models to explore policy implications of restructuring healthcare services for individuals with RA and OA.

1.8 Structure

In order to address the aims and objectives the thesis is structured into six interlinked chapters. A summary of the content of each chapter is provided below:

Chapter 2 explores the associations between travel time/ travel distance and health outcomes through a systematic review. It focuses on the question - *Are differences in travel time or distance to healthcare for adults in global north countries associated with an impact on health outcomes?* It describes the methods, reports the results and discusses and summarizes the findings. The findings feed into the case studies described in Chapters 3 – 4. This chapter addresses objective 1.

Chapter 3 describes the first case study used to explore the association between transport accessibility (measured in this case study using travel times and distance to healthcare) and differences in health/wellbeing. The case study uses the HES-PROMS dataset, which includes hospital appointment data for patients identified as having OA and a subset of these who have had a THR or TKR. This targets objective 3

Chapter 4 describes the profiles of those individuals who are part of the ELSA who have OA or RA. This includes how they travel and differences between the two MSK disease groups. The case study uses individuals health and well-being data and transport accessibility (measured in this case study using travel time/distance to the nearest healthcare facility and ease of access

to the GP/hospital) to explore the association. It considers whether there are any key differences across the regions of England in particular the London / outside London divide. This chapter targets objectives 2 and 3.

Chapter 5 brings together the case studies and systematic review results to test a number of different scenarios for provision of healthcare using a West Yorkshire population including the scenarios assessment of which hospital would minimise the travel times/ distances to healthcare and predicted changes in health outcomes. A method is tested to estimate individuals who are likely to not have access to a car. This chapter targets objective 4.

Chapter 6 (the final chapter) of the thesis draws together the findings from the previous chapters and brings out the key points and discusses the overall findings. Results of previous chapters will be interpreted collectively to develop overall conclusions. It discusses the strength and limitations of the thesis. The implications for public health research and policy will be identified, and recommendations for future research outlined.

2 Chapter 2: Systematic Review

2.1 Introduction

The aim of this chapter is to describe the systematic review that was undertaken to answer the research question - *Are differences in travel time or distance to healthcare for adults in global north countries associated with an impact on health outcomes?* (Study objective 1). The aim of this chapter is to gain a better understanding on whether travelling further to access healthcare facilities has a negative association with health outcomes. This systematic review brings together studies that have calculated patients travel to healthcare facilities following their attendance at the healthcare facility (revealed accessibility) and explored whether this is associated with health outcomes. The thesis was primarily interested in whether there was an association between travel time / distance and health outcomes, but also, secondly, an interest in the data and methods used by the studies. This would then be used to inform the data needed and methods of analysis for the two case studies presented in this thesis in Chapter 3 and Chapter 4. Parts of this chapter were published in Kelly et al. (2016) and Kelly et al. (2014).

2.2 Methodology

When designing the protocol for the systematic review it was considered whether it would be suitable to include a meta-analysis to pool results to give an average effect across studies. This was ultimately not included in the review protocol, as considerable heterogeneity was anticipated in the data with differences in populations, outcome measures (e.g. follow up, mortality), scale of distance to the healthcare facility, study designs (e.g. cohort, cross sectional) and disease groups (see Table 5) that would reduce the meaningfulness of the results. As noted in The Cochrane Collaboration (2011) *"if studies are clinically diverse then a meta-analysis may be meaningless and genuine differences in effect may be obscured"* (part 9.1.4).

The study followed the PICOS (Population, Intervention, Comparator, Outcome, Study Type) search design (Sackett et al., 1997). The population were adults accessing healthcare in Global North countries (studies were included from the following regions and countries: Northern America, Western Europe, Australia and New Zealand). Papers were restricted to studies in Global North countries to increase the relevance of the results to the UK case and application. The intervention and comparator were the distance and travel times to healthcare. The outcomes were any health outcomes (e.g. survival, mortality, and quality of life) and proxy measures for health outcomes (e.g. follow up attendance, utilisation of clinic). No restriction was made on study type or design. The following databases were searched: Web of Science,

MEDLINE, Embase, and Transport database, HMIC, and EBM Reviews for relevant papers in November 2014 and updated the search on 7th September 2016. As an example, the search strategy that was developed for MEDLINE is provided in Appendix 1.

All the titles and abstract were screened by myself and 20% were independently screened by Professor Claire Hulme (CH) to check for consistency. The key inclusion criteria were that the study quantified distance or travel time to healthcare AND identified whether there was an impact from this on health outcomes AND the assessment of travel time/ distance on the health outcome was the primary objective of the study. The study excluded papers:

- Including children (< 18 years old and maternity).
- Reporting only patient opinions and views.
- Reporting only one off emergency events or travel by different types of emergency vehicles including Myocardial Infarction and transfers between healthcare facilities.
- Reporting studies from Global South countries.

The full papers of studies that met the inclusion criteria were reviewed and data extraction and quality assessment completed. Reference lists of included papers were then reviewed to identify any additional studies. Any identified papers were subjected to the same review process described above. The quality assessment of the studies was undertaken using a modified version of the cohort studies Critical Appraisal Skills Programme (CASP) tool (CASP, 2015) linked to the PICOS terms. One of the critical aspects of the systematic review is that the quality of the paper needs to be robustly assessed. As the Centre for Reviews and Dissemination (CRD) state "There are many different checklists and scales, readily available…which can be modified to meet the requirements of the review, or a new detailed checklist, specific to the review maybe developed" CRD (2009) (p43). This review included a range of study types (e.g. cohort, cross sectional), which ruled out a number of existing checklists that have been developed for specific types of study and some specifically as part of a meta-analysis. There are positive and negative issues with most of the checklists. For example, the Newcastle-Ottawa Scale assesses the quality of non-randomised case control studies and separately cohort studies, so is not directly relevant in its current form for the range of papers and study types included in this review and has been shown to have poor levels of agreement between raters (Hartling et al., 2013). Currently no single approach to assessing study quality is appropriate to all systematic reviews. This review adapted the existing CASP checklist to quality assess the papers that were included in the review to make it specific to the key areas of bias that the study wanted to assess. This included key

components of the CASP tool for example: Did the study address a clearly defined question? Had a representative population been used? Was the exposure (distance or travel time) accurately measured to minimise bias? And the same for the health outcome; whether potentially confounding variables had been identified and included in the analysis. In addition the review included whether the funding source was external to the organisation and whether the study was peer reviewed. This was important as studies completed in-house may have an inherent tendency to be biased. CK extracted the data and assessed for quality, according to the study protocol and 20% were independently extracted and assessed by CH. No studies were excluded on the basis of the quality assessment.

The review protocol was developed and published on the PROSPERO database (Kelly et al., 2014).

2.3 Results

One hundred and eight studies met the inclusion criteria and were included in the review. The study flow diagram is provided in Figure 4, which shows that over 19,000 abstracts were initially identified and after removing duplicates (due to multiple databases being searched) 13,346 abstracts and titles were screened by hand. Two hundred and thirty were deemed to meet the study criteria. Full texts were accessed for these papers and screened of which 108 met the study criteria. For three papers the full papers were not accessible.

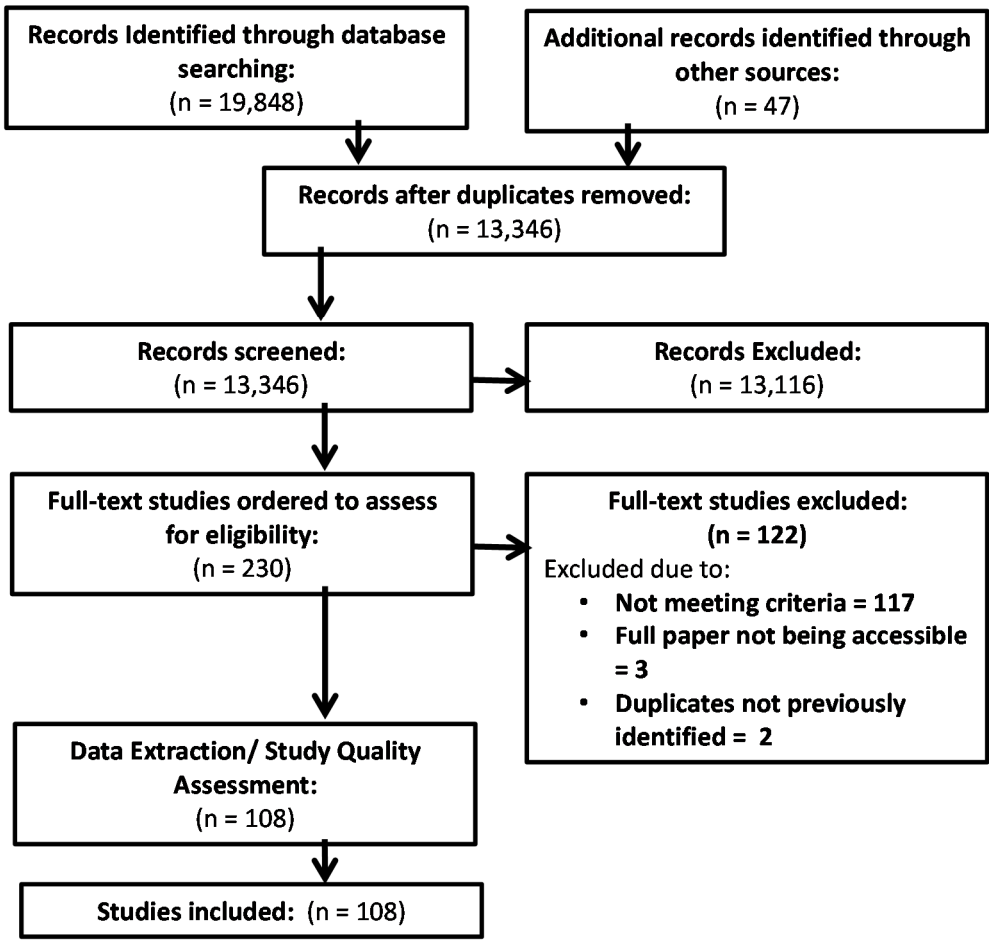


Figure 7: Review flow diagram

The studies covered a wide range of diseases groups, interventions and health outcomes. The results of the quality assessment are summarised in Table 1. Which shows that the main area of concern with regards to quality assessment was the funding source where – 37% of the studies were funded in-house or it was unclear how they were funded, which may introduce bias. The other question over the quality was whether the method used to calculate the distance/ travel time was reported accurately. Studies where no information on how the distances and travel times were calculated are highlighted in the results tables by study. No studies were excluded on the basis of this assessment.

Table 1 Quality Assessment of Studies n (%)

	Yes	No	Unclear/Partial
Did the study address a clearly focused question?	108 (100%)	0	0
Was the study population recruited in an acceptable way?	105 (97.2%)	0	3 (2.8%)
Did it include all the population or describe the population not included?	97 (89.8%)	7 (6.5%)	4 (3.7%)
Was the method used to calculate the distance/ travel time reported accurately?	85 (81.5%)	23 (18.5%)	0
Was the health outcome accurately measured to minimise bias?	108 (100%)	0	0
Have important confounding factors been taken account of in the design or analysis?	90 (83.3%)	17 (15.7%)	1 (1%)
Is the funding source external to the organisation?	68 (63.0%)	16 (14.8%)	24 (22.2%)
Was the research peer reviewed?	101 (93.5%)	0	7 (6.5%)

Studies were categorized according to the following 3 groups:

1. *Distance Decay Association* – Studies that showed evidence of an association between patients living closer to the healthcare facility and having better health outcomes/ higher access rates to the healthcare services compared to those living further away (these studies are presented in Table 2).
2. *Distance Bias Association* – Studies that showed evidence of an association between patients living further away from the healthcare facility and having better health outcomes/ higher access rates to the healthcare services compared to those living closer to the healthcare facilities (these studies are presented in Table 3).
3. *No Association* – Those studies that found no evidence of an association between distance from the health facility and health outcome (these studies are presented in Table 4).

Studies are organised within the results tables by disease type.

Table 2: Included studies that identified evidence of a distance decay association

Author Country & Date	Disease / Procedure	Source, Years & Sample size	Health Outcome	Distance/ travel time measurement	Origin and Destination	Summary of key results
Cancer Studies						
Abou-Nassar et al. (2012) USA 2012	Allogeneic Hematopoietic Stem Cell Transplantation	Clinical Operations and Research Information Systems database at DF/BWCC. 1996 - 2009. Sample = 1,912 (meeting the criteria of living < 6 hours to the treatment centre).	Overall Survival	Travel Time. Calculated using driving distance and average driving speeds along the road network Travel time was treated as a categorical variable using 3 groups: ≤40, 41 - 159, ≥160 mins and also a continuous variable. The range of distances was 2 - 358 mins.	Patients' Residence TO The transplant Centre	The study found that longer drive times to the transplant centres was associated with worse overall survival in patients alive and disease free after 1 year - This was only true using travel time as a continuous variable. They suggest this may be in part related to the lower number of visits in patients living further away after receiving the transplant.
Albornoz et al. (2016) USA 2015	Breast Reconstruction	National Cancer Database Included Patients who had a unilateral or bilateral mastectomy with or without reconstruction 1998 – 2011 1,031,343	The rate and method of breast reconstruction services	Straight-line Distance Straight-line distance. Using the "Great Circle Distance" in the database. Treated as a continuous variable. Average distance travelled for mastectomy without reconstruction – 27.1 miles & 34 miles with reconstruction.	Patients' Residence (zip code or city if zip code was unavailable) TO Hospital that reported the case.	The study found that patents had travelled further for breast reconstruction services than for mastectomy without reconstruction. Indicating a distance bias. Patients were more likely to have immediate breast reconstruction the further they had travelled (0-20 miles 13.9% reconstruction 101-201 miles 24.9%).
Anderson et al. (2013) USA	Colorectal Cancer	A set of cross sectional telephone survey of the population > 18 years in the USA. Taken from the Utah Behaviour Risk	Adherence to risk appropriate screening guidelines	Travel Time The study calculated 1 mile grid cells for the state of Utah and for each grid cell populated with individuals aged	Patients' Residence (determined using a 1 mile grid reference for the addresses)	The study found that residents living > 20 mins from the nearest colonoscopy provider were significantly less likely to be up-to-date with risk appropriate

2013		Factor Surveillance System. 2010 Sample = 2,844		50 or older they calculated the actual travel time to the nearest colonoscopy provider. This was then used to calculate a population weighted median travel time by zip code. Travel times was treated as a categorical variable and grouped into 3 categories: <10 minutes, 10 - 20 minutes & >20 minutes.	TO The nearest colonoscopy provider.	screening than those living < 10 mins from the nearest provider.
Athas et al. (1999) USA 1999	Breast Cancer	New Mexico Tumour Registry & The National Cancer Institute's surveillance Epidemiology and End Results. Patient Diagnosed 1994 – 1995Sample = 1,122	Receipt of radiotherapy following breast conserving surgery	Straight-Line Distance. Distance was treated as a categorical variable and split into the following categories: <10 miles, 10.0-24.9, 25.0-49.9, 50.0-74.9, 75.0-99.9, ≥100 miles.	Patients' Residence (street address (70% of cases) and centroid of residential zip codes (30%)). TO The nearest radiation treatment facility.	The study found that by controlling for age the likelihood of receiving radiotherapy following breast conserving surgery decreased significantly with increasing travel distance to the nearest facility. This was significant for distances >74.9miles compared to a base of <10miles.
Baade et al. (2011) AUSTRALIA 2011	Rectal Cancer	Queensland Cancer Registry (QCR) 1996 - 2007 Sample = 6,848	Cause specific survival	Road Distance and Travel Times. The distances were treated as a categorical variable using the following groups: < 50km, 50 - 99km, 100 - 199, 200 – 399 and ≥400km. The travel times were treated as a categorical variable using the categories of 0 -1hours, 2-4, 4-6, ≥ 6 hours	Patients' Residence TO The nearest radiotherapy facility	The study found that after adjusting for age, sex and stage at diagnosis, patients who lived 100 - 199km, 200-399km and 400km or more from a radiotherapy facility were 16%, 30% and 25% respectively more likely to die from cancer than patients living within 50km of such a facility. For every 100km increase in distance there was on average a 6% increase in risk of mortality. Similar results were found when travel time was used in the calculations, where patients living greater than 6 hours away were 22%

						more likely to die from cancer than those living 0- 1 hours away.
Brewer et al. (2012) NEW ZEALAND 2012	Cervical Cancer	New Zealand Cancer Registry. 1994 - 2005 Sample = 1,383	Cancer screening, stage at diagnosis and mortality	Travel Time and Road distance. The distances and travel times were treated as categorical variables using the following method of grouping - low - the lowest quartile, Medium - quartiles 2 and 3, High - records between the 75th and 95th percentiles and Highest - the highest 5% of records.	The 2001 census area unit for the patient (population weighted centroid) TO The nearest GP and nearest Cancer Centre	The study found that increased travel time/ distance was weakly associated with cervical cancer screening, stage at diagnosis and mortality.
Bristow et al. (2014) USA 2014	Ovarian Cancer	Californian Cancer Registry 1996 - 2006 Sample = 11,770	Treatment Adherence	Distance. (Does not say what method used) calculated using ESRI ArcMAP Distance was treated as a categorical variable and split into quintiles from < 5km up to > 80km.	Patients' Residence TO The treating hospital and the closest high volume hospital.	The study found that living > 80km (compared to < 9km) from a high volume hospital was associated with an increased risk of non-adherence to care plans (OR = 1.88, Confidence interval, 1.61 - 2.10). The study found that distance to a high volume hospital and distance to receive treatment could be used to predict whether patients would meet the guidelines for care for advanced stage ovarian cancer.
Burmeister et al. (2010) AUSTRALIA 2010	Lung Cancer	Queensland Cancer Registry. 2000 - 2004 Sample = 1,535	Delay in receiving radiation therapy Survival	Road Distance. (no info on GIS methods used) Distance was treated as a categorical variable using the groups of < 50km (where it was assumed that patients could travel on a daily basis from home) 50 - 200km (where it was assumed patients would go home for weekends only) and > 200km (where it was assumed that patients would	Patients' Residence (postcode) TO The nearest public radiation treatment facility.	The study found that waiting times for radiation therapy among lung cancer patients in Queensland was not associated with distance from home to the nearest public radiation treatment facility. The study found that those living > 200km away had slightly worse survival than those who lived < 50km.

				need to spend the duration of their treatment at the hospital).		
Campbell et al. (2001) UK 2001	Colorectal and Lung Cancer	Scottish Cancer Registry 1995 - 1996 Sample = 1,323	Presence of disseminated disease at diagnosis & emergency presentation or surgery.	Straight-line Distance. Distance was treated as a categorical variable using the groups of 0 - 5km, 6 - 37km, 38 - 57km and ≥58km. These were pre-defined cut off points.	Patients' Residence - (Census output area centroids) TO The nearest cancer centre.	The study identified that increasing distance from the nearest cancer centre was associated with a higher chance of disseminated disease at diagnosis and therefore lower chances of survival.
Campbell et al. (2000) UK 2000	Cancer (Lung, Colorectal, Breast, Stomach, Prostate, Ovary)	Scottish Cancer Registry 1991 - 1995 Sample = 63,976	One Year Survival	Straight-line Distance. Distance was treated as a categorical variable using the groups ≤ 5km, 6 - 13km, 14 - 23km, 24-37km and ≥38km.	Patients' Residence (postcode) TO The nearest cancer centre	The study found that increasing distance from the nearest cancer centre was associated with a reduced chance of diagnosis before death for stomach, breast and colorectal cancer and poorer survival after diagnosis for prostate and lung cancer.
Celaya et al. (2006) USA 2006	Breast Cancer	New Hampshire State Cancer Registry. 1998 - 2001. Sample = 2,861	Type of treatment received - either breast conserving surgery with radiography or Mastectomy	Straight-line Distance. Distances were treated as categorical variable using the groups <20 miles, 20 to <40, 40 to < 60, ≥60 miles. The mean distance was 15.1 miles (range 0.1–89.9).	Patients' Residence (Residential Address geocoded (80%) or zip code centroid (20%)) TO The nearest radiation treatment facility.	The study found that women were less likely to have breast conserving surgery with increasing distance from the nearest facility. They were also less likely to have radiation therapy the further away they lived - if they had previously undergone breast conserving surgery.

Cramb et al. (2012) AUSTRALIA 2012	Breast Cancer and colorectal cancer	Queensland Cancer Registry. 1996 - 2007 Sample = 26,390 Males = 14,690 and Females = 11,700	Survival and premature deaths	Travel Time. Shortest travelling time by road. Travel time was grouped into 3 categories based on practical considerations. < 2hours, 2 - 6 hours and >6 hours	Centroid of the patients' statistical local area TO The closest radiation facility	The study concluded that the proportion of premature deaths was higher for those living >2 hours from a treatment facility for breast cancer. Colorectal patients living > 6 hours from a treatment facility had poorer outcomes than those in the 2- 6 hour category, but this was not statistically significant.
Crawford et al. (2009) UK 2009	Lung Cancer	Northern and Yorkshire Cancer Registry and Information Service. 1994 - 2002 Sample = 34,923	Diagnosis and form of treatment	Travel Time. Calculated using ArcGIS 9.2 using average car speeds along the shortest route. Travel time was treated as a categorical variable - dividing the patients into equal quartiles. Patients were then put into 1/ 16 groups that combined 4 quartiles of travel time and 4 quartiles of deprivation.	Patients' Residence TO The closest hospital providing diagnostic access.	The study found that patients living in the most deprived areas were least likely to receive histological diagnosis, active treatment and thoracic surgery. They found that travel time "amplified this effect "– patients in the most distant & most deprived group had the worst outcomes.
Dejardin et al. (2014) FRANCE & ENGLAND 2014	Colorectal cancer	3 Cancer registries (Calvados, Cote d'Or and Saone et Loire) and 1 cancer registry in England (Northern and Yorkshire). 1997 - 2004 Sample = 40,613	Survival	Travel Time. Using ArcGIS in England and Mapinfo in France. The study used road map databases using legal speed limits by road class. Travel time was treated as a categorical variable using the 5 groups of 0 - 5 mins, 6 - 20 mins, 21 - 40mins , 41 - 90 mins and ≥ 91mins for travel times to the nearest cancer centre & nearest radiotherapy unit and 0 - 5, 6 - 10, 11-15, 16 - 40 and	Patients' Residence (at the time of diagnosis) TO The nearest cancer centre, radiotherapy centre and hospital.	The study identified (unadjusted analysis) that travel times were significantly associated with survival, as patients living further from healthcare resources had a worse chance of survival than those living closer. When including material deprivation in the model this effect was removed.

				≥41mins for travel to the nearest hospital.		
Dupont-Lucas et al. (2011) FRANCE 2011	Colorectal Cancer	Clinical trials in Calvados Normandy and Cote-d'Or Burgundy - testing the diagnostic properties of two types of faecal occult blood test. June 2004 - December 2006 Sample = 4,131	Colonoscopy uptake	Road Distances. Calculated using Mapinfo 9.1 combined with CHRONOMAP 2.1 based on the MultiNet Map database (Tele Atlas). Distances were grouped into quartiles: 0 - 5.5km, 5.5 - 13.8, 13.8 - 22.1 & 22.1 - 52.3km.	Patients' Residence (Home Address) TO The nearest gastroenterologist / or regional capital /or clinical trial centre	The study found that distance to the regional capital and distance to the clinical trial centre were independently associated with colonoscopy uptake. Distance to the nearest gastroenterologist was not found to be significant.
Engelman et al. (2002) USA 2002	Breast Cancer	The Health Care Financing Administration enrolment database to identify each fee for service Medicare eligible women in Kansas. - Medicare Claims data. 1997 – 1998 Sample = 117,901	Mammogram attendance	Straight-line Distance. Distance was treated as a continuous variable.	Patients' Residence (zip code) TO The nearest permanent & mobile mammography sites.	The study showed that increasing distance from a permanent mammogram facility was significantly associated with decreased mammogram rates. After controlling for age, race and education this relationship was still significant. OR = 0.97 for each 5 mile increment.
Fournel et al. (2010) FRANCE 2010	Colorectal Cancer	Burgundy Registry. 1990 - 1999. Sample = 6220 colorectal adenoma patients and 2,387	Colorectal adenoma detection	Distance. (method not reported) Distance were included as a categorical variable using groupings of <5km, 5 - 15km and >15km.	Patients' Residence TO The GP, hepatogastroenterologist (HGE), and physician (not	The study found that incidences of colorectal cancer were not significantly associated with distance to the GP, HGE, or the physician. The study did find a significant interaction between place of residence and the distance to the GP and place of residence and the HGE. The impact of the distance to the physicians

		colorectal cancer patients.			clear whether these were the nearest)	was significant for patients living in rural areas.
Giuliani et al. (Giuliani et al., 2016) Italy 2016	Breast Cancer	Romagna Cancer Registry Patients were included if they had a diagnosis of in situ and invasive cancer between 1990 – 2000 735	Compliance with yearly mammography and /or Clinical breast examination over 10 year follow up period.	Travel Times. Calculated using Google Maps. Travel time was split into categories ≤15 mins, 16 – 30 and >30. The study also considered the altitude of the patient's residence.	Patients' Residence (assumed not stated) TO The centre for cancer prevention	The study found that patients were less likely to have a yearly check-up (over the 10 years) if they had to travel >30 mins compared to ≤15 mins.
Goyal et al. (Goyal et al., 2015) USA 2015	Breast Cancer	Breast Cancer Disparity Cohort Study (New Jersey) African American and white patients diagnosed with early stage breast cancer. 2005 - 2011 623	Mastectomy OR Breast conserving surgery followed by adjuvant radiation therapy	Travel Distance and Travel Time Shortest travel time/ distance was calculated using Google Maps. Distance and travel times were treated as categorical variables and split up into quartiles. Travel distance <3.2miles, 3.2-5.6, 5.7-9.2 and >9.2miles. Travel times <9 mins, 9-13 mins, 14-19 mins and >19 mins.	Patients' Residence TO The radiation facility where patients received Radiation Therapy (where unavailable-surgeons were contacted by phone and the referral obtained)	The study found that patients living further away from the radiation therapy centre in the categories of 5.7-9.2miles and >9.2miles compared to < 3.2 miles (REF) were significantly more likely to have a mastectomy than breast conserving surgery followed by RT. Patients living > 19mins compared to <9 mins were also more likely to receive a mastectomy rather than breast conserving surgery.
Haddad et al. (Haddad et al., 2015) USA	Bladder Cancer	Urban tertiary cancer centre (single site) 2007 – 2013	Short and long term survival after radical cystectomy	Shortest Driving Distance Calculated using Google Maps Distance was treated as a categorical variable. Using the categories of < 50	Patients' Residence TO	The study found that increasing distance to the facility was a significant predictor of 90 day mortality (univariate model) and was still significant after controlling for nodal status. For long term survival

2015		406		miles, 50 – 100, 100.1 – 150 and >150 miles. Median distance 37.3miles	The Treatment Facility (Single Site)	distance was significant for those travelling >150miles versus <50miles for the univariate model.
Haynes et al. (2008) New Zealand 2008	Cancer (prostate, colorectal, breast, lung, melanoma)	New Zealand Ministry of Health 1994 - 2006 Sample = 1,383	Late diagnosis and likelihood of death	Travel Time. Travel time was treated as a categorical variable and split into 4 categories (Low, medium, High, Highest) low - lowest quartile, medium (quartile 2 and 3) high records between 75% and 95 percentiles and highest - highest 5% of records.	Population weighted centroid of the 2001 census area units (CAU represent approx. 2300 people) TO The nearest cancer centre and nearest GP	The study had mixed results. After controlling for the extent of the disease, poor survival was associated with longer travel times to the GP for prostate cancer and longer travel times to the nearest cancer centre for colorectal, breast and prostate cancers, but not lung cancer or melanoma. The study found that the disease tended to be less advanced in patients who lived further from the cancer centres and living further from a GP practice was not associated with a later stage diagnosis.
Holmes et al. (2012) USA 2012	Prostate Cancer	Physician workforce study in North Carolina & North Carolina Central Cancer Registry on patients diagnosed with incident cancer linked to Medicare claims. 2004 - 2005 Sample = 2,251	Delayed Diagnosis	Straight-line Distance. Distance was treated as a categorical variable and used 3 groups of: 0 - 10 miles, 11 - 20miles and > 20 miles.	Patients' Residence (zip code centroid of patient residence) TO The nearest urologist	The study found that increasing distance to an urologist was significantly associated with higher risk of prostate cancer at diagnosis, which was higher for black patients.

Huang et al. (2009) USA 2009	Breast Cancer	Kentucky Cancer Registry. 1999 - 2003 Sample = 12,322	Diagnosis Stage	Road Distance. Distance was treated as a categorical variable using the groups - <5 miles, 5 - 9, 10 - 14 and ≥15 miles	Patients' Residence (78% were geocoded based on street address. 15% using the centroid of the 5 digit zip code and 7% using the 5 digit zip code + 2 or + 4 digits) TO The nearest mammogram centre	The study found that patients diagnosed with advanced stage diagnosis had longer average travel distances than early stage diagnosis. After controlling for age, race, insurance and education the odds of advanced diagnosis were significantly greater for women living ≥15 miles compared to those living <5 miles.
Jethwa et al. (2013) USA 2013	Breast Cancer	Hospital Records. 2007 Sample = 260 (women were excluded if they were non-white or had a previous cancer diagnosis)	Stage of breast cancer at diagnosis, survival	Distance (Unknown calculation). Distance was treated as a categorical variable using the following groups: < 15 miles, 15 - 44 miles, 45 - 59 miles, and ≥60 miles.	Patients' Residence TO The treating hospital	The study found that the further the distance the more likely women were to be diagnosed at a later stage and the more likely women were to have a mastectomy. The study found no association between travel distance, age at diagnosis, receipt of radiotherapy, or 5-year survival.
Jones et al. (2008b) UK 2008	Breast colorectal, lung, ovarian and prostate cancer	Northern and Yorkshire Cancer Registry and Information Service (NYCRIS) 1994 - 2002 Sample = 117,097	Survival (whether patients were alive or dead on 31st March 2005) and late stage diagnosis	Travel Times. Calculated using average car travel speeds by road class on the road network. Travel time was treated as a continuous variable. The study also determined: -whether patients were within 800m of an hourly bus service for rural patients. Straight-line distance to the nearest cancer centre, car journey to the closest railway station, travel time to the GP and first referral hospital.	Patients' Residence TO The GP, Hospital of first referral and closest cancer centre	The study found that late stage diagnosis was associated with increasing travel time to the GP for breast and colorectal cancer and risk of death was associated with increased travel time to the GP for prostate cancer. The study identified residential deprivation was significantly related to survival.

Jones et al. (2010) UK 2010	Cancer (Colorectal, ovary, breast, prostate)	Northern and Yorkshire Cancer Registry Information Service. 1994 - 2002. Sample = 3,536	Whether or not the diagnosis was made at death. (Diagnosis date = death date)	Road Distance and Travel time Calculated using average travel speeds using the road network. Straight-line distance and whether patients lived within 800m walking distance of an hourly weekday bus service & whether there was a local community transport scheme. Travel time to hospital was modelled as a categorical variable using quartiles.	Patients' Residence (postcode) TO The nearest healthcare provider postcode/ Nearest GP	The study found that the highest odds of being diagnosed at death were for those living in the least accessible quartile of travel time for the hospital, but this association was only statistically significant for colorectal and ovary cancer. The study found that living in the least accessible travel time quartile to the GP had the highest odds of being diagnosed at death, but was not statistically significance. Breast and prostate cancer patients living closer to a frequent bus service were significantly less likely to be diagnosed at death.
Jones et al. (2008a) UK 2008	Breast, Colon, Rectum, Lung, Ovary and Prostate Cancer	Northern and Yorkshire Cancer Registry (NYCRIS)1994 - 2002 Sample = 117,097	Patients receiving surgery, chemotherapy or radiotherapy	Travel Time. Travel time was modelled as a categorical variable and divided into quartiles.	Patients' Residence (home postcode) TO The nearest hospitals providing treatment.	The study identified an inverse relationship between travel time and treatment take up. Patients were less likely to receive radiotherapy the further they lived from the hospital. Lung cancer patients were less likely to receive surgery & Lung and rectal patients were less likely to receive chemotherapy.
Kerschbaumer et al. (2012) AUSTRIA 2012	Glioblastoma Multiforme (GBM) - malignant brain tumor	Medical Records 1990 - 2009 Sample = 208	Survival (Months)	Shortest Road Distance. Distance was treated as a continuous variable. Average distance was 75km (range 1 - 870km)	Patients' Residence (home address) TO The neuro oncological centre	The study found that distance to the neuro oncological centre had a significant effect on overall survival. Patients were less likely to be treated with chemotherapy following surgery the further they lived away from the centre. The study found that when a new treatment was introduced that

						could be administered locally this removed this effect.
Kim et al. (2000) UK 2000	Colorectal cancer	South and West Cancer Intelligence unit. 1991 - 1995 Sample = 4,962	Survival All-cause mortality	Straight-line Distance. Distance was treated as a categorical variable using the following groups - ≤10 km, > 10 to ≤ 20 km, > 20 to ≤ 30 km and > 30km.	Patients' Residence(postcode) TO The treating hospital	The study found that those travelling ≥ 30km from the treating hospital had significantly poorer survival, but that those living 20 - 30 km away appeared to be least at risk. Implying a U shape in terms of risk.
Lavergne et al. (2011) CANADA 2011	Palliative Radiotherapy (PRT)- Cancer	Oncology Patient Information System (Nova Scotia) 2000-2005 Sample = 13,494	PRT Treatment & Consultation	Travel Time. Calculated using "GIS" and average vehicle speeds by road type. Travel time was treated as a categorical variable using 4 categories: 0 - <30 mins, 30 - < 60 mins, 60 - < 120 mins and 120 - 214mins.	Patients' Residence (postcode at death) TO The nearest treatment centre	The study found that Palliative radiotherapy use declined with increasing travel time and community deprivation.
Lin et al. (Lin et al., 2015) USA 2015	Colon Cancer (stage III)	National Cancer Data Base Patients aged 18 – 80 who had a colectomy within 3 months of diagnosis and survived > 6months 2007 – 2010 34,694	Receipt of adjuvant chemotherapy within 90 days of a colectomy.	Road Distance Calculated using Google Maps. Distance was treated as a categorical variable using the following categories; 0 – 12.49miles, 12.5-49.9, 50-249, and ≥250miles. For patients flying in from outside the USA for treatment straight-line distance was used. Average distance travelled to the oncologist was 12.5 miles.	Patients' residence at diagnosis (centroid of zip code) TO Reporting facility (90% had treatment in the reporting facility.	The study found that patients travelling in the further two categories 50 – 249miles and ≥250 miles had a lower likelihood of receiving chemotherapy than those travelling less than 12.5miles.

Maheswaran et al. (2006) UK 2006	Breast Cancer	Anonymised data April 1998 - March 2001 Sample = 34,868	Breast Screening Uptake	Road Distance. Distance was treated as a categorical variable and a continuous variable. Distances were grouped into 2 km bands. <2km, 2 to <4, 4 to <6, 6 to<8 and ≥8	Patients' Residence (postcode) TO The screening location that they were invited to attend.	The study found that when analysed as a continuous variable there was a small but significant decrease in uptake of breast cancer screening with increasing distance - adjusted odds ratio of 0.87 (95% CI -0.79 - 0.95) for a 10km increase in distance. The strongest effect on breast screening uptake was deprivation.
Meden et al. (2002) USA 2002	Breast Cancer	Medical Records. 1999 – 2000 Sample = 66	Difference in treatment technique – Modified Radical Mastectomy vs Breast Conserving Therapy	Distance. Unclear method. Likely to be straight-line. Distance was treated as a categorical variable. Distances were split into <45 miles and ≥45miles. Average distance was 61.6 miles (range 0 – 138 miles)	Patients' Residence TO The nearest radiation oncologist facility.	The study found that access to breast conserving surgery declined as travel distance increased. Patients living further away were more likely to have had a mastectomy.
Nattinger et al. (2001) USA 2001	Breast Cancer	National Cancer Institute - Surveillance, Epidemiology and End Results (SEER) Registry. 1991 - 1992. Sample = 17,729	Receiving Breast conserving surgery (BCS) OR receiving BCS with radiotherapy.	Straight-line Distance. Distance was treated as a categorical variable - using the groups of < 5miles, 5 to <10, 10 to < 15, 15 to < 20, 20 to <30, 30 to <40, ≥ 40 miles for receipt of BCS vs mastectomy and the groups of 0 to <10, 10 to <20, 20 to <30, 30 to <40 and ≥ 40 miles for receipt of radiotherapy among BCS patients.	Patients' Residence (Census tract) TO The nearest hospital with a radiotherapy facility (centroid of the zip code)	The study found a statistically significant decline in the likelihood of patients undergoing breast conserving surgery living ≥15 miles from a hospital with radiotherapy facilities when compared to those living < 5miles. They also found a statistically significant result for those patients living ≥ 40 miles having a reduced rate of radiotherapy following Breast conserving surgery.
Onitilo et al. (2014) USA	Breast Cancer - Mammography Screening	Local Cancer Registry. 2002 - 2008. Sample = 1,421	Stage at diagnosis	Road Distance and Travel Time. Calculated using ESRI ArcGIS. Distances were treated as continuous & categorical variables	Patients' Residence (street address for the patients (where available) /centroid of patients zip code where not)	The study found that women who missed none of their 5 annual mammograms lived a median of 15 minutes from the nearest facility, whilst those who missed 5 /5 lived a median time of 27 minutes.

2014				Travel times were split into the categories of 0 - 5 mins, 5 - 15 mins, 15 - 30 mins, 30 - 60 mins, ≥ 60 mins.	TO The nearest mammogram facility and the actual facility attended.	The study found that patients living >30 miles to the closest facility were less likely to be screened for breast cancer in the winter months.
Panagopoulou et al. (2012) GREECE 2012	Breast Cancer	Hellenic Cooperative Oncology Group (clinical trials in 6 Greek cities) 1997 - 2005 Sample = 2,789 (women)	Survival	Road Distance and Travel Time. Distance was grouped into < 300km and ≥ 300km. Travel time was grouped into < 4 hours and 4+ hours. Additional tests using the following distance categories: <50, 50 - 149, 150 - 249, 250 - 349, 350+km.	Patients' Residence (98.7% of the sample using residential address, or the city centre of the city of residence, for the remaining 1.3% the weighted mean of available distances to each destination hospital) TO The treating hospital	The study found that travelling a distance >300km and travel time of 4 + hours were significantly associated with worse survival outcomes (HR = 1.37 & 1.34) base <300km and <4h respectively.
Punglia et al. (2006) USA 2006	Breast Cancer	The linked Surveillance, Epidemiology and End Results- Medicare (SEER) database. 1991 - 1999. Sample = 19,787	Receiving Radiation Treatment after a Mastectomy	Straight-line Distance. Distance was treated as a continuous and categorical variable. Using categories of <25, 25-50, 50-75 and 75+ miles. 5 patients living more than 900 miles away were excluded, as were patients in Hawaii. The median distance was 4.83 miles.	Patients' Residence TO The nearest radiation treatment facility.	The study found that increasing distance to the nearest radiation treatment facility was associated with a decreased likelihood of receiving radiation treatment therapy. For each extra 25 miles of travel was associated with declining odds of receiving radiation. The effect of distance showed as being stronger where patients were >75 years and those travelling 75+ miles compared to <25 miles.
Schroen et al. (2005) USA 2005	Breast Cancer	Virginia Cancer Registry. Patients diagnosed 1996 - 2000. Sample = 20,094	Mastectomy rates VS Breast conservation and radiation therapy	Straight-line Distance. Distance was modelled as a categorical using 10 miles, 10 - 25, > 25 - 50 and > 50 miles (range 0 - 84miles)	Patients' Residence (zip code) TO The nearest radiation therapy facility.	The study found a higher rate of mastectomy the further distance the patient lived from the nearest radiation therapy facility (after controlling for tumour size, year of diagnosis and age).

Scoggins et al. (2010) USA 2012	Breast cancer Lung cancer Colorectal cancer	Washington State Cancer Registry Washing state Medicaid enrolled at time of diagnosis or within 6 months 1997 – 2003 4,413	Stage at diagnosis (local or regional/distant Likelihood of surgical treatment. Time to first surgical treatment (number of days since diagnosis)	Driving Time and Driving Distance Calculated using MapQuest (www.mapquest.com) Distance and travel time were treated as categorical variables.	Patients' residence (9 digit zip code used where available) TO Patients general practice/ primary care provider	The study found that later stage diagnosis for breast cancer was associated with increased driving time (but not lung or colorectal cancer). A significant result was found for the time to first treatment for colorectal patients where after controlling for socio demographic factors, year of diagnosis, and cancer stage for every 1 hour increase in drive time, time to treatment was delayed by 5.9 days. The study concluded that there was no evidence that drive time was a better predictor than driving distance.
Temkin et al. (2015) USA 2015	Gynaecologic cancer	University of Maryland Medical Centre (single site) Nov 2009 – Dec 2011 152	Completion of recommended adjuvant therapy	Travel Time and Distance Calculated using the Google Maps. Treated as continuous variables. Distance range 0.3 – 12 miles. Travel time range 2 – 169 mins.	Patients' Residence (zip code) TO The hospital attended	The study found mixed results - 87% of the sample completed the therapy. 11 people did not complete and 8 died before completion. They found that those patients living <10 miles or >50 miles were less likely to complete treatment (13% of the sample). Those living further were more likely to die before completing, but also had higher comorbidities.
Thomas et al. (2015) Ireland 2015	Colorectal Cancer	Irish National Cancer Registry Patients who were diagnosed and still alive. Oct 2007 – Sept 2009	Quality of life following survival (measured using QLQ-30)	Distance Unspecified method Distance was treated as a categorical variable. Distances were divided into teriles. 1 and 2 were combined (≤30.81km) & group3 (>30.81km). Group 3 was then defined as living "remotely" from the hospital.	Patients Residence (at time of diagnosis) TO The hospital they were treated at.	The study assessed the impact of distance on the components of the QLQ-30 and by gender. The study found that living a greater distance from the hospital was associated with – lower physical functioning and role functioning (for women and not men). For men living remotely (>30.8km) had a significant negative impact on their self-

		Survey - 1273 sent, 496 returned				reported health and quality of life, but not for women.
(Tracey et al., 2015a) Australia 2015	Lung Cancer	New South Wales Central Cancer Registry 2000 - 2008 11,457 (split into diagnosis – localised stage, regional and distance)	Survival (at one and five years)	Straight-line Distance Calculated using the 'Great Circle distance calculator' Distance was treated as a categorical variable using 3 groups of 0-39km, 40-99km and 100+ km.	Patients' Residence TO The nearest specialist public hospital (NASH) & nearest general hospital.	The study found that patients living further away from the specialist hospitals were less likely to attend the specialist hospital & less likely to have curative surgery – Resulting in lower survival rates. Patients who lived further away & were admitted to a specialist hospital and received curative surgery were more likely to survive at 5 years than those not receiving curative surgery.
(Tracey et al., 2015b) Australia 2015	Lung Cancer (localised non-small cell)	NSW Central Cancer Registry Patients admitted with localised stage at diagnosis ≤12 months following diagnosis 2000-2008 Sample = 3,240	Receiving Surgical resection within 12 months of diagnosis	Straight-line Distance Calculated using the 'Great Circle distance calculator' Distance was treated as a categorical variable using 3 groups of 0-39km, 40-99km and 100+ km.	Patients' Residence TO The nearest specialist public hospital (NASH) & closest general hospital.	The study found that 51% of patients living >100km from a specialist hospitals didn't have surgery compared to 38% of those living <40km. Patients living further from the specialist hospitals were more likely to be treated at a general hospital and less likely to receive potentially curative surgery.
Tracey et al. (2014) AUSTRALIA 2014	Epithelial Ovarian Cancer	New South Wales Cancer Registry. 2000 - 2008. Sample = 3411	Survival	Straight-line Distance. Distance was treated as a continuous variable and categorical variable for which it was grouped into equal quartiles - 0 - 5km 5.1-9.0km, 9.1-27.0, 27.1 - 187.0, 187.1+	Patients' Residence TO The closest gynaecological oncology hospital	The study concluded that there was an increasing trend in the unadjusted hazard of death model with increase in distance to the closest public gynaecological Oncology hospital. The study reported that whilst they had used the closest hospital in their calculations only 37% of their sample had used their closest hospital.

Wang et al. (2008b) USA 2008	Breast Cancer	Illinois Cancer Registry 1998 - 2000 Sample = 30,511 (9,077 were classed as late stage)	Late stage diagnosis	Straight-line Distance and Travel Time. Travel times were calculated using the ArcInfo network analysis module – using the minimum road distance when taking account of travel speed.	Patients' Residence (Population weight centroid of zip codes) TO The closest mammography facility & the closest GP.	The study found that travel time to mammography services had no statistically significant association with late stage risk. The study did find that as travel time to the nearest GP increased patients were more likely to have a later stage diagnosis.
Kidney studies						
Bello et al. (2012) CANADA 2012	Diabetes & Chronic Kidney Disease (jointly)	Alberta Kidney Disease Network & Provincial Health Ministry 2005 - 2009 Sample = 31,377	All-cause mortality, all cause hospitalisation, renal outcomes	Road Distance. Distance was treated as a categorical variable. Using the following 6 categories 0-50, 50.1 - 100, 100.1 - 200 and >200km	Patients' Residence (6 digit postal code) TO The nearest nephrologist	The study found that when using a base of <50km, patients living >50km were less likely to visit a nephrologist, less likely to have follow up measurements of A1c and urinary albumin within a year. Plus have a higher change of all cause hospitalisation and all-cause mortality.
Bello et al. (2013) CANADA 2013	Patients with proteinuria (Kidney Damage)	Alberta Health and Wellness, Alberta Blue Cross, the Northern and Southern Alberta Renal Program and the provincial laboratories of Alberta. 2002 - 2009 Sample = 1,359,330	A range of health outcomes.	Shortest Road distance. Distances were treated as a categorical variable using the groups : 0-50, 501 - 100, 100.1 - 200 and >200km.	Patients Residence (6 digit home postal code) TO The nearest nephrologist.	The study found a statistically significantly higher incidence of stroke and hospitalisations in those travelling a greater distance, but no association for the other outcome measures
Cho et al. (2012)	Peritonitis	ANZDATA Registry	A range including - Peritonitis Free - Survival, first peritonitis	Road Distance. Calculated using Google Maps.	Patients' Residence	The study found that living ≥100 km away from the nearest peritoneal dialysis unit was not significantly associated with time to first peritonitis episode. The study did find an

AUSTRALIA 2012	(Kidney)	2003 - 2008 Sample = 6,610	episode, staphylococcus aureus peritonitis.	Distance was treated as a categorical variable using the groupings - < 100km and ≥100km.	TO The nearest peritoneal dialysis unit.	association between living ≥ 100km away from the nearest unit and increased risk of Staphylococcus aureus peritonitis.
Judge et al. (2012b) UK 2012	Renal Replacement Therapy (RRT) - Kidney	UK Renal Registry (UKRR) 2007 Incident population = 4607 Prevalent population = 36,775	Renal Replacement Therapy Incidence and Prevalence	Travel Time. Average speeds were assigned to roads and GIS transportation software Base Trans CAD used to estimate the minimum travel time. Travel time was treated as a continuous and categorical variable split into 4 groups: < 15mins, 15 - 29mins , 29 – 45, & 45+ mins	Patients' Residence (Centroid of the CAS Ward (average 2670 people in each ward)) TO The nearest Dialysis Unit	The study found that patients living >45 min travel time from the nearest dialysis unit were 20% less likely to commence or receive renal replacement therapy than those living < 15 min.
Miller et al. (2014) CANADA 2014	Chronic Kidney Disease	Canadian Organ Replacement Registry (CORR) 2000 – 2009 Sample = 26,449	Incident Central Venous Catheter (CVC) use	Straight-line Distance. Distances were divided into 3 groups <5km, 5 - 20km and >20km	Patients' Residence (home postal code at dialysis initiation TO The nearest dialysis centre	The study found that increasing distance was associated with increased use of central venous catheters in incident dialysis patients.
Moist et al. (2008) USA 2008	Kidney Dialysis	Dialysis Outcomes and Practice Patterns Study (DOPPS) - questionnaire 1996 - 2001 (DOPPS 1) 2002 - 2004 (DOPPS 2) Sample = 20,994 (from 7 countries, France, Germany, Italy, Japan, Spain, UK and USA)	HRQoL, Mortality, Adherence, withdrawal, hospitalisation and transplantation	Travel Time. The survey asked the question - How long does it take you to get to your dialysis unit or centre (1 way)? Respondents could answer ≤15mins, 16 - 30, 31 - 60 and >60mins. They were also asked how they usually travelled to the dialysis unit.	Patients' Residence TO The dialysis centre attended	The study found that longer travel times were associated with a greater adjusted relative risk of mortality. Health related quality of life scores were lower for those with longer travel times when compared with travelling < 15mins.

Thompson et al. (2012) USA 2012	Kidney Disease	United States Renal Data System. Jan 1995 – 2007 Sample = 726,347 (the study excluded patients with missing or invalid postcodes)	Mortality	Shortest Driving Distance. Distance was treated as a categorical variable. Using 5 categories: 0-10 miles, 11-15, 26-45, 46-100 and >100miles. The categories correspond to the 0 – 75th , 75-95th, 95th -99th, 99th-99.9th and >99.9th percentiles.	Patients' Residence (5 digit zip code at time of first renal replacement, dialysis or transplant) TO The closest Haemodialysis Centre	The study found that distance, but not living in a rural area was associated with increased mortality. The adjusted model identified a statistically significant hazard ratio between the reference case (0-10milles) and the 11-25 miles and >100miles categories, but not for other distance categories.
Thompson et al. (2013) US 2013	Kidney	United States Renal Data System 2001 - 2010 Sample = 1,784	Quality of Care Indicators (90 days following haemodialysis therapy and at 1 year)	Shortest Road Distance. Distance was treated as a categorical variable. Using the following categories: ≤50km, 50.1 - 150km, 150.1 - 300, >300km.	Patients' Residence (5 digit zip code) TO The closest nephrologist.	The study found that patients were less likely to have seen a Nephrologist 90 days prior to starting haemodialysis therapy, and were more likely to have a sub optimal levels of phosphate control the further they lived from a haemodialysis centre.
Tonelli et al. (2007a) CANADA 2007	Kidney Failure	Canadian Organ Replacement registry 1990 - 2000 Sample = 26,775	Mortality	Shortest Road Distance Calculated using postal data converted using Melissa (2019)and entered into ArcGIS. Distance was treated as a categorical variable using the groups of: <50km, 50.1 - 150km, 150.1 - 300 and >300km	Patients' Residence (6 digit postal code) TO The practice location of the patients' nephrologist.	The study found that remote dwelling Canadians with kidney failure were significantly more likely to start renal replacement on Peritoneal Dialysis (PD) and switch to PD if their initial dialytic option was haemodialysis. The adjusted rates of death and the adjusted hazard ratios were significantly higher in those living ≥50km from the nephrologist compared to those < 50 km.
Tonelli et al. (2007b) Canada	Kidney (Haemodialysis)	Canadian Organ Replacement Register 1990 - 2000 (when the sample started dialysis) Sample = 18,722 (random sample of 75%	Mortality (from all causes) Then split by cause - infectious or cardiovascular	Shortest Road Distance Calculated using ArcGIS 9.1. Distance was treated as a categorical variable using the following groups -	Patients' Residence TO The practice location of the attending nephrologist.	The study found that mortality associated with haemodialysis was greater for patients living further from their attending nephrologist. This was particularly evident for infectious causes.

2007		of the patient population)		0-50km, 50.1-150km, 150.1-300km, >300km		
Diabetes Studies						
Littenberg et al. (2006) USA 2006	Type 2 diabetes	Vermont Diabetes Information System. Adults completed postal surveys and were interviewed at home. Years Unknown Sample = 781 (131 insulin users & 650 non users)	Glycaemic Control Insulin Use	Shortest driving distance Calculated using ESRI ArcView 3.3 and a geographic data set of roads from Tele Atlas. Distance was treated as a continuous and categorical variable. Distances were grouped as <10km & > 10 km	Patients' Residence (home address) TO Primary care facility	The study found that insulin users had shorter driving distances to the healthcare facility than non-users. Longer driving distances were associated with poorer glycaemic control. The OR for those using insulin, living <10km, having glycaemic control was 2.29 (CI 1.35, 3,88; p = 0.002).
Strauss et al. (2006) USA 2006 (Data cross over with Littenberg et al 2006))	Diabetes	Vermont Diabetes Information system. Adults completed postal surveys and were interviewed at home (23% of the contacted population) July 2003 - March 2005 Sample = 973 (794 non insulin users & 179 insulin users)	Glycaemic Control (for insulin and non-insulin users)	Shortest Road Distance Calculated using a road network in ArcvIEW 3.3. Distance was modelled as a categorical variable. Patients were split into 3 equal groups <3.8km, 3.9 - 13.3km, ≥13.3km	Patients' Residence (home address) TO Primary care facility used.	The study identified that longer driving distances from the patients' home to the site of primary care were associated with poorer glycaemic control.

Zgibor et al. (2011) USA 2011	Diabetes	Seven diabetes management centres in Southwestern Pennsylvania. Jun 2005 - Jan 2007 Sample = 3,369	Controlled vs uncontrolled diabetes	Road Distance. Driving distance using the network analyst tool in ArcGIS. Distance was treated as a continuous and categorical variable. Distance was divided into 2 categories ≤10 miles and >10 miles. The average distance was 13.3 miles.	Patients' Residence (home address) TO The diabetes treatment centre attended.	The study found that living > 10 miles away significantly contributed to lower levels of glycaemic control for diabetes patients. Those who lived ≤ 10 miles from the diabetes treatment facility were 2.5 times more likely to have improved their levels of glycaemic control between their first and last visits.
Transplant Studies						
Goldberg et al. (2014) USA 2014	Liver Transplant	Veterans Health administrations integrated, national electronic medical records linked to organ procurement and transplantation network 2003 - 2010 Sample = 50,637	Being waitlisted for a liver transplant, having a liver transplant and mortality	Straight-line Distance. Distance was treated as both a continuous and categorical variable. 5 distance categories: 0 - 100miles, 101-200, 201-300, 301-500, >500miles	Veterans Admission (VA) Centre TO The Veterans Admission Transplant Centre (VATC)	The greater the distance from a VATC or any transplant centre was associated with a lower likelihood of being put on a waiting list or receiving a transplant and greater likelihood of death.
Redhage et al. (2013) USA 2013	Liver Transplant	Hospital Data and HRQOL (Health Related Quality of Life) survey. Dates unknown Sample = 706	Longitudinal HRQOL was measured using the SF-36 Health Survey and a rolling enrolment process.	Distance [unspecified] Distance treated as a continuous variable. The distance range was 0 – 2261 miles and average 179.	Patients' Residence (home address) TO The transplant centre	The study found that increased distance to the transplant centre was associated with a decreased post-transplant physical HRQOL, but that there was no association between distance and pre-transplant HRQOL.

Thabut et al. (2012) USA 2012	Lung Transplant	Transplant Registry 2001- 2009 Sample = 14,015	Listing for a transplant, receipt of a transplant and survival.	Straight-line Distance. Using ArcGIS Software. Distance was treated as a categorical variable using two different sets of groupings. The following groups - 0 - 50 miles, 51 - 100 miles, 101 - 150 miles, 151 - 200 miles and > 200 miles. Secondly percentiles	Patients' Residence (centroid of the residential zip code) TO The nearest adult lung transplant centre	The study found that the distance from a lung transplant centre was inversely associated with the hazard of being listed (both before and after the introduction of the lung allocation score). Once waitlisted distance from the closest centre was not associated with differences in survival.
Zorzi et al. (2012) USA 2012	Liver Transplant	United Network for Organ Sharing Jan 2004 – July 2010 Sample = 5,673	Mortality & being dropped from a waiting list due to being too sick.	Straight-line Distance. Distance were calculated using ww.zip-codes.com Distance was considered as a continuous & categorical variable and divided into the following 3 groups: <30miles, 30 -60 miles and >60 miles	Patients' Residence TO The nearest liver specialised transplant centre & nearest 300 bed hospital.	The study found that increased distance from a specialised liver transplant centre was associated with an increased likelihood of death. The likelihood of wait list drop out was significantly higher for patients living > 30 miles from the specialised liver transplant centre.
Obesity Studies						
Jennings et al. (2013) UK 2013	Obesity (Laparoscopic adjustable gastric banding - LAGB)	Hospital Database. < 2010. Sample = 227	Compliance with follow up appointments.	Road Distance. Calculated using Google Maps. Distance was treated as a continuous variable. The average distance for perfect attenders is 15.3 miles and non-attendees are 21.1.miles.	Patients' Residence (Home Address) TO The treating hospital	The study identified that compliance with follow up following LAGB is associated with better weight loss. Patients living closer to the treating hospital were more likely to regularly attend follow up. The study reported longer public transport journey times in the non-attending group - but did not include this in the analysis.

Lara et al. (2005) USA 2005	Obesity	Gundersen Lutheran Medical Centre data. Sept 2001 - April 2003 Sample = 150	Compliance with follow up at 3, 6 ,9 and 12 month appointments	Straight-line Distance. Distances were treated as a categorical variable using groups: <50 miles 50 - 100 miles and >100 miles	Patients' Residence (zip code TO The Clinic they were treated/ followed up at.	The study found that travel distance from the clinic did not significantly affect compliance at the initial follow-up, 3-month, and 12-month appointments. However, distance did affect compliance at the 6-month appointment and significantly affected compliance at the 9-month appointment.
Sivagnanam and Rhodes (2010) UK 2010	Obesity - Laparoscopic adjustable gastric band (LAGB)	The Norwich Spire Hospital. October 1997 - March 2009. Sample = 150	Follow up and weight loss	Distance. Method not reported. Distance was treated as a categorical variable and split into the following distance groups <10, 10 - 20, 20 - 30 and > 30. (all miles) 87% of the patients lived < 50 miles from the hospital.	Patients' Residence TO The Norwich Spire Hospital.	The study found that patients attended fewer follow up clinics, as distance increased from the patient's home address. The percentage estimated weight loss was lowest in the group that lived furthest from the hospital, but this was not statistically significant.
Mental Health Studies						
McCarthy et al. (2007) USA 2007	Mental Health - Schizophrenia or bipolar disorder	National Veterans Affairs (VA) administrative data. Patients who received a diagnosis of schizophrenia or bipolar disorder in the year Oct 1997 - Sept 2008 and survived the year. Sample = 163,656	Continuity - measured by time to first 12 month gap in VA health services utilisation	Straight-line Distance. Distance was treated as a continuous variable. Average distance to the nearest provider was 11.8 miles.	Patients' Residence (population centroid of the patients zip code) TO The nearest VA providers of substantial psychiatric services or community based outpatient clinics serving at least 500 unique patients where at least 20% were mental health visits.	The study found that patients who had a 12 month gap in VA services utilisation were more likely to live further away. Living ≥25 miles from VA care was associated with a greater likelihood of a gap in VA health utilisation. The hazard ratio associated with each 5 miles further from psychiatric services was 1.011.

Joseph and Boeckh (1981) CANADA 1981	Mental Health	Provincial health records 1976 Sample = 1767 inpatients & 883 outpatients	Seriousness of diagnosis	Distance. Distance from Peterborough Ontario. They do not provide any other information on method of calculation.	Patients' Residence TO Peterborough Ontario	The study concluded that severity of diagnosis increased as distance travelled increased.
Skarsvag and Wynn (2004) NORWAY 2004	Mental Health Psychiatric	Regional population & actual patient data from the Stokmarknes Clinic in Nordland 1992 - 1996 Sample = 10,996 (total population) & Sample = 1,834 (treated population)	Use of an outpatient clinic	Travel Time. Calculated from information gathered from local bus and ferry companies. The study treated travel time as a categorical variable using the cut off of 35 minutes.	All residential addresses in the local area & actual patient attendees. TO The outpatient clinic at Stokmarknes.	The study found that a significantly higher proportion of those living < 35 mins from the clinic had used the clinics services than > 35mins.
Other studies						
Allen et al. (2016) USA 2016	Sleep Apnea	University of British Columbia Hospital Sleep Disorders Clinic Included referred patients whose travel times were < 1 hour. May 2003 – July 2011. Sample = 1,275	Severity of obstructive sleep apnea	Travel Time. Calculated using DMTI routing data and the ArcGIS Network analyst function. Travel time was treated as a continuous variable and categorical variable. The mean travel time was 20.8 mins. The cut point for the categorical variable was the mean time.	Patients' Residence (postcode) TO The sleep disorder clinic	The study found that travel time to the sleep clinic was a predictor of obstructive sleep apnea severity (controlling for sex, age, obesity and education). Every 10 min increase in travel time was associated with an increase of 1.4 events per hour in the apnea-hypopnea index.

Arcury et al. (2005) USA 2005	Non specific - Health care visits	Survey of adults in 12 rural Appalachian North Carolina Counties. Personal interviews in participants homes. 1999 - 2000. Sample = 1,059	Number of regular check-up care visits, chronic care visits and acute care visits	Straight-line Distance. Distance to the healthcare facility was based on respondents stating which hospital, clinic or doctor they would normally go to for "a really bad emergency", A less serious emergency, and for regular care.	Patients' Residence (Survey at respondents homes) TO The self-reported hospital, GP, clinic that they would normally go to for a really bad emergency, a less serious emergency or for regular care.	The study found that distance was significantly associated with the number of regular check-up care visits and chronic care visits. Distance was not associated with acute care visits. They identified that those people with a driving license had an estimated 1.58 times more regular care visits and 2.3 times more chronic care visits.
Ballard et al. (1994) USA 1994	Non-specific.	Medicare hospitalization data (MEDPAR) 1998 Sample = 13,596	30 day mortality	Distance No information in paper on specific method. Distance was split into the categories of <10 miles and ≥ 10 miles.	Patients' Residence (zip code) TO The hospital attended (zip code)	The study found that increased distance from the patient's residence to the hospital that they were treated in was independently associated with higher 30 day mortality rates.
Chou et al. (2014) USA 2012	Coronary Atery Bypass Graft (CABG)	Pennsylvania HealthCare Cost Containment Council 1995 - 2005 Sample = 102,858	In hospital mortality and readmission	Straight-line distance. Distance was treated as a continuous variable. Average distance 14.9 miles.	Patients' Residence (Centroid of the patient's residential zip code) TO The admitting hospital	The study found that high risk CABG patients living further from the admitting hospital had increased in-hospital mortality.
Etzioni et al. (2013) USA 2013	Any Surgical Operation	National Surgical Quality Improvement Project (NSQIP) database - for a large tertiary care institution. 2006 – 2009 Sample = 6,938	30 day surgical outcomes	Distance No information on method. Distances were treated as a categorical variable and split into quintiles. The average distance was 226 miles.	Patients' Residence (zip code centroid) TO The tertiary hospital attended.	The study found that patients who lived closer were less likely to have a serious complication at 30 days and had better outcomes than predicted.

Evans et al. (Evans et al., 2016) USA 2016	HIV with Severe sepsis	University of Virginia Clinical data repository 2001 – [not stated] Sample = 74	In hospital Mortality	Distance Method unspecified. Dichotomised into ≤40miles and >40 miles	Patients' Residence (assumed) TO The University of Virginia Ryan White HIV clinic	The study found that after adjusting for severity of illness and respiratory failure, patients living >40 miles from the clinic had a fourfold increased risk of in-hospital mortality compared to ≤40 miles.
Haynes et al. (1999) UK 1999	Inpatient Episodes	Regional Health Authority. 1991 - 1993 Sample = 470,650 acute episodes, 13,425 psychiatric episodes and 36,909 geriatric episodes.	Healthcare episodes	Straight-line Distance. Distance was treated as a continuous variable. The furthest distance to the GP was 8km and to the acute hospitals 41km.	Patients' Residence (weighted centroid of the patients ward) TO The nearest district general hospital. & nearest GP surgery	The study found that after controlling for key confounders distance to hospital was a significant predictor of hospital episodes, especially psychiatric episodes. The study found that distance to the GP was only significantly associated with reductions in acute episodes in hospital.
Jackson et al. (2013) USA 2013	Colorectal Surgery	The National Surgical Quality Improvement Programme Database. May 2003 - April 2011 Sample = 866	Length of Stay	Road Distance with the shortest travel time. Distance was treated as a continuous variable. The mean distance travelled was 146.9 miles (range 2 - 2984). The study transformed distance and length of stay onto the log scale due to non-normal distributions.	Patients' Residence (5 digit zip code) TO The hospital treated at (5 digit zip code).	The study found that in the adjusted model increased travel distance from a patient's residence to the hospital was associated with an increase in length of stay.
Jackson et al. (2014) USA 2014	Elective Pancreatic Surgery	Local National Surgery Quality Improvement database. 2005 - 2011 Sample = 243	Length of Stay	Road Distance (shortest travel time) Distance was treated as a continuous variable. The distances ranged from 3 - 3006 miles.	Patients' Residence (5 digit zip code) TO The hospital treated at (5 digit zip code)	The study found (in the general model) that for each additional 100 miles travelled, the length of hospital stay increased by 2%.

Jones et al. (1999) UK 1999	Asthma	Regional Deaths System for East Anglia. 1985 - 1995 Sample = 768 (of which asthma was the underlying cause of death in 365 of these).	Mortality	Travel Times. Travel times were treated as categorical & continuous The groupings used for travel to the GP were 0 - 4mins >4 - 6 mins, >6 - 9 mins and ≥ 9mins. The minimum travel time was 3 minutes and the maximum 20.8 minutes. The categories to the hospital were 0 - 10, > 10 - 20, > 20-30, ≥ 30mins. The minimum time to the hospital was 4.4 minutes and the maximum 54.7 minutes.	Patients Residence (starting point measured at the ward level-average number of households = 2,726) TO The nearest GP and the nearest acute hospital with over 200 beds.	The study identified an association between asthma mortality and increasing travel time to the nearest acute hospital. The study found no relationship between distance to the GP and asthma mortality rates.
Lake et al. (2011) UK 2011	TB - treatment with full course of anti TB therapy	National enhanced TB surveillance system (ETS) 2001 - 2006 Sample = 21,954	Completion of TB Treatment	Road Distance. Distance was treated as a categorical variable using the groups of < 7.3km and > 7.3km.	Patients' Residence (postcode) TO The TB treatment facility	The results indicate that attending a TB centre with low case load or greater distance was associated with poorer treatment outcomes. The study identified that distance to a TB treatment centre was insignificant for patients native to the country (UK).
Lankila et al. (Lankila et al., 2016) Finland 2016	Primary Healthcare Attendance	Northern Finland 1966 Birth Cohort Questionnaire administered 1997 (cohort were all 31 years old) Sample = 4,503	Use of local health centres	Shortest Road Distance Calculated using the Finish road network data (Digiroad) using ESRI ArcGIS 10. Distance was treated as a categorical variable using 0-1.9km, 2 – 4.9 km 5.0-9.9 km and ≥10.0km	Patients' Residence TO The municipalities health centre facility (or where there were more than one – the closest was used)	The study found that the number of people attending health centres and mean number of visits declined with distance for people living in rural areas, but this was not significant, but the opposite was the case for the sub group in urban areas travelling ≥10.0km compared to 0-1.9km.

Monnet et al. (2008) FRANCE 200	Hepatitis C	Registry Data 1994 - 2001 sample = 1,938	Hepatitis C detection rates	Road Distance. Calculated using Chrono Map in MapInfo with the 1997 Michelin light road network table (which includes major roads). Distance was treated as a continuous variable.	Patients' Residence (geometric centroid of the patients municipality of residence) TO The GP (geometric centroid of municipality)	The study found that the detection rate for Hepatitis C decreased in each of the studies socioeconomic clusters as distance to the GP increased.
Prue et al. (1979) USA 1979	Alcohol Abuse	Jackson Veterans Administration Hospital. Years Unknown, Sample = 40.	Aftercare attendance.	Road Distance. Calculated as total miles. Split into "miles to " the nearest highway and "miles on" the nearest highway. Distance was treated as a continuous variable. The range of distances was (12 - 378 miles).	Patients' Residence (home address) TO The aftercare facility	The study found that the number of "miles to" and "miles on" the highway significantly affected the probability of attendance at an alcohol abuse aftercare appointment. Distance to the major highway was more predictive of attendance than the miles on the major highway.
Singh et al. (2014) CANADA 2014	Cardiac	Brunswick Cardiac Centre. 2004 - 2011. Sample = 3,897	30 day rates of adverse events following non-emergency cardiac surgery	Road Distance. Distance was treated as a categorical variable using the following groupings: 0-50km, 50 - 100km, 100 - 150km, 150 - 200km, 200 - 250km and >250km.	Patients' Residence (Home address) TO The Cardiac Surgery Centre	The study found that increased distance from the cardiac surgery centre was independently associated with a greater likelihood of experiencing an adverse event at 30 days.

Table 3: Included studies identifying evidence of a distance bias association

Author Country and Date	Disease / Procedure	Source, Years & Sample size	Health Outcome	Distance/ travel time measurement	Origin and Destination	Summary of key results
Cancer Studies						
Bristow et al. (2015) USA 2015	Ovarian Cancer (Advanced Stage)	Californian Cancer Registry 1996 – 2006 11,765	Mortality	Straight-line Distance Calculated using ESRI ArcMap 10.0. Distance was treated as a categorical variable using quintiles. Categories for hospital attended: <5km, 5-9, 10-16, 17-31, ≥32km. Categories for nearest high volume hospital: <9km, 9-17, 11-20, 21-49 & ≥80km. 80% of patients travelled ≤28.3km to the hospital they were treated at. 80% of patients were ≤ 79.6km to the nearest high volume hospital.	Patients' Residence TO The hospital treated at and the nearest high volume hospital.	The study found that travelling 5-9km, 17-31 km and ≥32km to the hospital compared those travelling <5km (reference case) was associated with a reduction in the risk of mortality. After controlling for hospital size and adherence to treatment guidelines 5-9km and 17-31km compared to the reference case were still significant. The opposite case was found for distance to the nearest high volume hospital for patients travelling ≥80km compared to the reference case of <9km. This was no longer significant after controlling for adherence to treatment guidelines.
Lamont et al. (2003) UK 2003	Cancer	4 phase II chemo radiotherapy studies conducted at the University of Chicago. 1993 - 2000 Sample = 110.	Survival	Distance. Driving miles (using an "internet based mapping engine"). Distances were treated as a categorical variable and split into two groups ≤ 15 miles (45 patients) and > 15 miles (67 patients)	Patients Residence (exact address) TO The University of Chicago hospital	The study found a positive association between the distance that patients travelled and survival. Those living > 15 miles had only 1/3 of the hazard of death than those living ≤15 miles. With every 10 miles that a patient travelled the hazard of death declined by 3.2%.

Lenhard Jr et al. (1987) USA 1987	Multiple Myeloma	Centralised Cancer Patient Data System. 1977 - 1982. Sample = 1,479	Survival	Distance. Distance was treated as a categorical variable using the following groups - 0 - 9 miles, 10 - 49 miles, 50 - 149 miles, and ≥ 150miles	Patients' Residence (zip code) TO The treating centre (zip code area)	The study found that survival improved with increasing distance travelled to treatment centres.
Lipe et al. (2012) USA 2012	Bone Marrow Transplant for Multiple Melanoma	Dartmouth Hitchcock Medical Centre transplant registry 1996 - 2009 Sample = 77	Survival (OS and progression free survival)	Straight-line Distance. Calculated using Melissa (2019) Distance was treated as a continuous variable and categorical variable split into the groups of < 50miles and > 50 miles	Patients' Residence TO The Dartmouth Hitchcock Medical Centre	The study found that increasing distance from the transplant centre was associated with improved overall survival. The authors identified that this could be due to a referral bias, but could also be due to a healthier and more motivated groups of patients living further away.
Wasif et al. (2014) USA 2104	Gastrointestinal Cancer	National Cancer Database. 2003 – 2009 Sample = 77	Survival	Distance. [Method not specified] Distance was treated as a continuous variable and categorical variable split into the groups of <50 miles and >50 miles	Patient' Residence (zip code centroid) TO The treatment facility zip code centroid	The study found that adjusted hazard ratios were significantly lower for patients travelling > 50 miles compared to < 50 miles. This was true for liver, oesophageal and pancreatic cancer. They concluded that those that travelled > 50 miles to the treatment facility had lower 30 day mortality rates.
Other Studies						
DeNino et al. (2010) USA 2010	Obesity (Gastric Band)	Teaching hospital patients Nov 2008 - Nov 2009 Sample = 116	Follow Up Compliance and Weight Loss	Road Distance. Calculated using Google Maps. Distance was treated as a continuous variable. The average distance to the hospital was 39.5 miles.	Patients' Residence (exact address) TO The hospital treated at.	The study found a weak relationship between increased travel distance to the hospital and increased weight loss. Travel distance was found not to be significant for attending follow up visits.

Table 4: Included studies identifying no association

Author Country	Disease / Procedure	Source, Years & Sample size	Health Outcome	Distance/ travel time measurement	Origin and Destination	Summary of key results
Cancer Studies						
Celaya et al. (2010) USA 2010	Breast Cancer	New Hampshire State Cancer Registry (NHSCR) 1998 - 2004 Sample = 5,966	Stage at diagnosis	Driving Time and Road Distance. Calculated using ESRI ArcGIS and data from ESRI on street networks, posted speed limits and driving distance. Distance and travel time were treated as categorical variables. Using the following groupings: < 5 miles, 5 - <10 miles, 10 - < 15.0 miles, ≥15 miles. For travel time < 5 mins, 5 - < 10 mins and ≥ 10 mins	Patients' Residence (Addresses of patients were geocoded to an exact street address(91%) or to the zip code centroid if only a post office box or rural route address was available.) TO The nearest mammography facility.	The study identified no significant association between later stage breast cancer and travel time to the nearest mammography facility. They did identify that there was good access (patients did not have to travel a large distance) to mammography facilities in the area studied, as shown by the categorical groupings.
Cosford et al. (1997) UK 1997	Cancer	Cancer Registry 1991 Sample = Number of patients in each local authority district attending hospital with a diagnosis of cancer and the number who received radiotherapy in that year.	Radiotherapy uptake	Travel Time. Modelled used to obtain off peak drive times + use of a commercially available computer programme Travel time was treated as a continuous variable. Maximum travel times 1 hour.	Population weighted centroid of 14 different local authorities TO The nearest cancer centre serving the area.	The study found no significant relationship between overall radiotherapy uptake and travel times.

Crawford et al. (2012) UK 2012	Colorectal Cancer	Northern and Yorkshire Cancer Registry and Information Service. 1994 – 2002 Sample = 39,619	Stage of diagnosis & receipt of treatment	Travel Time. Shortest road route and average driving speeds along the routes by road class. Travel times were split into quartiles.	Patients' Residence TO The nearest hospital providing diagnostic and surgical treatment services for bowel cancer.	The study found no effect of travel time distance on stage of diagnosis or receipt of treatment. They also found no interaction effects between deprivation and travel time.
Gunderson et al. (2013) USA 2013	Cervical Cancer	Medical Records 2006 - 2011 Sample = 219	Overall Survival Progression free survival	Straight- line Distance. Distance was treated as a categorical variable. Using the following groups: <30 miles and >30 miles	Patients' Residence (zip code) TO The treating hospital (if the patient underwent surgery) otherwise the radiation centre.	The study found no significant difference between patients travelling <30 miles and those travelling >30 miles for survival. They found that non Caucasians were less likely to travel > 30 miles.
Heelan and McKenna (2011) IRELAND 2011	Cancer	Melanoma Database. 2000 - 2009 Sample = 106	Breslow Thickness	Driving Distance. The automobile Association route planner was used to estimate distance travelled by road. Data was treated as a categorical variable using the groupings of < 30km and >30km. The median distance was 33.3km (range 0.2 - 123.12km)	Patients' Residence TO The hospital attended.	The study found no significant association between distance travelled and Breslow thickness on presentation. The study concluded that this could have been due to the type of patients in the sample (high number of thick lesions) in both distance categories.
Henry et al. (2013) USA 2013	Breast Cancer	US North American Association of Central Cancer Registries. Patients diagnosed 2004 - 2006	Stage at diagnosis	Travel Times. The study calculated 3 accessibility measures including shortest road network drive time. This used the	Road nearest the population weighted centroid of each census tract TO	The study found that after adjusting for poverty there was no impact of distance on late stage diagnosis. They found that poverty was independently associated with late stage diagnosis.

		Sample = 174,609		NAACCR shortest path calculator (NAACCR, 2019) Travel times were treated as categorical variable using the following groups - ≤ 5 mins, > 5 - 10, > 10 - 20, > 20 - 30, > 30. 93% of the breast cancer cases lived < 20 mins from the nearest mammography facility and only 2.8 % lived > 30mins.	The nearest FDA certified mammography facility	
Henry et al. (2011a) USA 2011	Breast cancer	10 state population based cancer registries - covering 30% of the population of the USA. Patients diagnosed 2004 - 2006 Sample = 161,619	Stage at Diagnosis	Travel Time. Travel time was modelled as both a continuous and categorical variable. There were 7 categories ranging from < 10 mins to ≥ 60 mins. 76% of the women lived <20 mins from their diagnosing facility & 93% < 20mins from the nearest mammography facility.	Patients' Residence (residential street address (87%) or postal delivery area centroid (8%). TO The diagnosing facility and nearest facility.	The study concluded that increased travel time was not a determinant of late stage diagnosis. They found that insurance status, race and poverty were associated with risks for a late stage diagnosis of breast cancer.
Khera et al. (2016) USA 2016	Hematopoietic cell transplantation	Fred Hutchinson Cancer Research Centre/ Seattle Cancer Care Alliance 2000 – 2010 2,849	Non relapse mortality Relapse mortality Survival at 200 days	Distance Method unspecified. Distance was treated as a continuous and categorical variable. Categories ≤100km, 100- 500, 500, 1000 and > 1000km from the centre were used. Categories of <170km and ≥170 km were used to assess mortality. Median distance 263km (range 0 – 2740km)	Patients' Residence (zip code) TO The transplant centre (Fred Hutchinson Cancer Research Centre)	The study found no relationship between increasing distance and non-relapse mortality, relapse mortality and survival at 200 days. The study does state that patients are required to stay within 30 minutes of the hospital for the first 80 to 100 days, which allows them to be closer (for most patients than their residential address) for any early issues. After this patients were followed up via telemedicine in addition to travelling to the clinics.

Meersman et al. (2009) USA 2009	Breast Cancer	California Health Interview survey 2001 Sample = 4,249	Mammography uptake	Straight-line Distance. Distances were treated as categorical variable and split into the following quartiles: 0 - 0.53 miles, 0.54 - 1.07 miles,1.09 - 1.82 miles and 1.83 - 26.5 miles. The study also calculated the number of public transit stops within 3 miles of the respondent and split these into quartiles.	Patients' Residence (70% of the sample were geocoded based on the nearest street to their residence, 30% to their zip code centroid). TO The nearest mammography facility.	The study did not use the distance calculations in the final model (as they were not significant)- but instead used mammography density within 2 miles of a patient's residence instead - which was found to be significant. The number of bus stops within 3 miles was not significant. This indicated that density of mammography facilities and not distance was the critical factor.
Ragon et al. (2014) USA 2014	Allogeneic hematopoietic stem cell transplantation (HSCT)	Transplant data team and medical records 2006 - 2012 Sample = 299	Survival	Straight-line Distance. Distance from the transplant centre was split into 2 groups of <170km and >170km. This represented a cut off at 75th percentile.	Patients Residence (Zip code at the time of the transplant) TO The medical centre where they were treated.	The study found that distance did not impact on the overall survival rate.
Sauerzapf et al. (2008) UK 2008	Breast Cancer	Northern and Yorkshire Cancer Registry Information Service. 1994 - 2002 Sample = 6,014	Breast conserving surgery vs mastectomy & whether patient had received radiotherapy following breast conserving surgery.	Travel Time. Fastest Travel time using the road network. Using ArcGIS and the Meridian digital road network. Sections of the road were assigned average car travel times. Distances were treated as categorical variables using the categories of ≤30 mins, 30 - 60 mins > 60 mins. The study also collected information on those living within 800m of a frequent bus service.	Patients' Residence (postcode) TO The closest hospital where radiotherapy was available.	The study found that the choice of breast conserving surgery or receiving radiotherapy was not associated with the estimated travel time. They did find that travel time to radiotherapy was only significant as a predictor of surgery choice for patients living >800 m from a frequent bus service.

Schroen and Lohr (2009) USA 2009	Breast Cancer	Virginia Cancer Registry 2000 - 2001 Sample = 8,170	Invasive tumour size at diagnosis	Shortest Road Distance. Calculated using ArcGIS. Distance was treated as a continuous variable. The average distance was 5.7 miles and only 5% of the patients lived >20 miles away.	Patients' Residence TO The nearest mammography facility.	The study found that distance to the nearest mammography facility had no consistent relationship between invasive tumour size at diagnosis in the adjusted model. They found that only advanced age was a predictor of invasive tumour size at diagnosis
Other Studies						
Firozvi et al. (2008) USA 2008	Liver Transplant	Medical Centre Transplant Database. 2002 - 2005 (censor date 2005) Sample = 166.	Listing status, time required to list, survival once listed, transplantation and 1yr post transplantation survival.	Travel Time. Calculated using Yahoo! Maps. Travel time was treated as a categorical variable using > 3 hour and ≤3 hour. 38 people had travel times > 3. The range of travel times was 0 - 7 hours.	Patients' Residence (where not available the patients home town or city centre) TO The specific transplant centre	The study found that those patients living > 3 hours away from a transplant centre had comparable outcomes to those living closer.
Leese et al. (2013) UK 2013	Diabetes Related Foot Disease	Three linked data sets. Scottish Care Information Diabetes Collaboration - Tayside Regional Diabetes Register, Foot ulcer dataset, Amputation dataset. 2004 - 2006 Sample = 15,983. 670 (with new foot ulcers) 99 (with an amputation)	Occurrence of a new foot ulcer or amputation	Travel Time (using road distance) Travel time was treated as a continuous variable. The average time to the GP was 6.48 minutes, average time to the local hospital was 28.47 minutes.	Patients' Residence TO The local hospital clinic and local GP	The study concluded that distance from the GP or hospital clinic and lack of attendance at community retinal screening did not predict a foot ulceration or amputation. They did find that being socially deprived was significantly associated with foot ulceration.

Markin et al. (2011) USA 2011	Pulmonary Arterial Hypertension	PAH Disease Management (REVEAL). Years Unknown. Sample = 638	Delayed diagnosis	Distance. (method not reported) Distance was treated as a categorical variable using the grouping of < 50miles vs >50 miles.	Patients' Residence TO The pulmonary hypertension (PH) centre	The study concluded that distance from the PH centre was not shown to be associated with a delayed diagnosis, lower likelihood of early treatment with an IV/SC prostacyclin analog, or a worse functional class at diagnosis.
Rodkey et al. (1997) USA 1997	Heart Transplant	Transplantation hospital charts, local hospital records and direct patient and family contact. 1984 - 1995 Sample = 312	Rejection episodes, No. of endomyocardial biopsies, ED visits, hospital admissions, infections, coronary allograft vasculopathy, malignancies re-transplantation and death	Distance. Distance was calculated using the Rand McNally TripMaker Version 1.1. Distance was treated as a categorical variable using the groups 0 - 150miles 151 - 300 miles and >300miles. 207 patients lived in group 1, 69 patients lived in group 2 and 36 in group 3. (range 2 - 1218 miles)	Primary city of residence TO The transplant centre	The study concluded that long distance management of heart transplant recipients is successful and is not associated with an increase in adverse outcomes. Patients living further away had similar results to those in the closest category (0 – 151 miles).
Stoller et al. (2005) USA 2005	1-Antitrypsin (AAT) deficiency	The results are based on a 4 page mailed out survey to AAT deficient individuals. Achieving a 38% response rate. 2003 Sample = 1,851 (Achieving a 38% response rate)	Diagnostic delay	Distance. Calculated using GIS software Distance was treated as a categorical variable using the groups of < 50 miles and ≥ 50 miles to the CRC. 38% of the survey respondents lived within 50 miles of a CRC.	Patients' Residence (zip code) TO The nearest designated clinical resource centre.	The study found that neither urban residence nor living near a centre with expertise (living within 50 miles) was associated with a shortened delay in diagnosis.

Swan-Kremeier et al. (2005) USA 2005	Eating Disorder	Contact records, clinical records and appointment records of patients at a treatment centre. Unknown date Sample = 139 (37 completers & 102 drop outers)	Attendance Patterns and Treatment Attrition	Straight-line Distance. Distance was treated as a continuous variable. The average distance for completers was 43.9 miles and the average distance for drop outers was 29.8 miles.	Patients' Residence To The treatment centre	The study concluded that distance travelled to the treatment site was not significantly different between the two groups (drop outers and completers).
Tonelli et al. (2006) CANADA 2006	Kidney transplantation	Canadian Organ Replacement Registry. Patients starting dialysis 1996 - 2000 (followed until Dec 2001) Sample = 7,034	Likelihood of Transplant	Distance (No information on distance calculations). Distance was treated as a categorical variable using the groups - < 50km, 50.1 - 150km, 150.1 - 300km and > 300km.	Patients' Residence (at the time of starting dialysis) TO The nearest transplant centre	The study found that the likelihood of a transplant was not affected by the distance to the nearest transplant centre.

The studies came from a wide range of countries the majority 56% from the USA, with 17.6% from the UK and 8.3% from Australia and New Zealand (combined). Over 50% of the studies reported on cancer (55% in Table 2, 83% in Table 3 and 53% in Table 4) with the majority being breast or colorectal studies. Other diseases and outcomes are summarised in tables 2 – 4 and table 5. The studies covered a wide range of contexts and travel requirements for patients. Studies that identified a distance decay association ranged from a very localised cohort of patients - average distances to the healthcare facility of 13.3 miles for treatment for diabetes (Zgibor et al., 2011), to > 6 hours travel in Canada for breast and colorectal cancer survival (Cramb et al., 2012) , to > 300km for remote kidney dialysis (Tonelli et al., 2007a), and an inter country study with a range of 1km – 870km for treatment for malignant brain tumour (Kerschbaumer et al., 2012) . These differences reflect both the geographical sizes of the countries in question and the need to travel for specialist treatment. There was no obvious difference in the distances and travel times between the three groups (distance decay, distance bias and no association).

A range of associations were found. Seventy seven percent of the included studies were classified as a distance decay association; six studies reported a distance bias association and 19 identified no association. The studies were diverse in nature with five of the studies (Table 3) reporting a positive association between increasing travel distance and better survival rates for cancer (Lamont et al., 2003, Bristow et al., 2015). Lipe et al. (2012) concluded that survival rates were higher for those travelling further to the transplant centre potentially due to referral bias, but also patients living further away being healthier and more motivated. Other effects identified by the review include the study by Kim et al. (2000) who highlighted a U shaped all-cause mortality relationship. When the data was split into three categories of distance travelled, those in the middle (20 – 30 km) category had lower all-cause mortality than those living in the closer or further away categories. This indicated that there was something different about this geographical area and the people living in it. This effect was evidence in other papers, but not at statistically significant levels.

A wide variety of methods and data (e.g. registry data, patient surveys, hospital data) were used to explore the association. There were differences in the patient origins and healthcare destinations used to determine the patient journeys. The majority used the patient's address (full address/postcode/ zip code) as the origin for the journey, but others used the centroids of larger geographical areas (Judge et al., 2012b; Haynes et al., 2008; Brewer et al., 2012; Jones et al., 1999), or the referring hospital (Goldberg et al., 2014) or the city of residence (Rodkey et

al., 1997) . It was recognised that for the longitudinal studies there was a potential for patients to move address, but no studies used differing residential locations where people moved house to calculate the distances and travel times. For example, Dejardin et al. (2014) applied the residential location at the time of diagnosis and assumed this remained constant during treatment. Forty – eight percent of the studies had access to data on the nearest healthcare facility to the patient, with the remainder using the actual healthcare facility attended. Bristow et al. (2014) and Henry et al. (2011b) calculated both the nearest and actual facility attended. All the studies that showed health outcomes improved as distance/ travel time increased used the actual healthcare facility attended by the patients in their study.

The methods used for calculating travel distance / travel time in the studies ranged from straight-line distance (Euclidean distance), travel distance using a road network (either shortest distance or shortest travel time); travel speed using the shortest distance by road network (with and without adjusted road network speeds) or patients' self-reported travel time. As shown in Table 1 9% of the studies did not clearly state how they had calculated this variable. One hundred percent of the studies in the distance bias association group calculated travel distance, 77% in the distance decay association group and 63% in the group that identified no association.

The results presented by disease group and health outcome measure and decay, bias and no association categories, as shown in Table 5. This shows the same patterns of the majority of studies reporting significant statistical associations between a distance decay effect and differing outcomes can be observed. As can be seen clearly the majority of studies focus on cancer (breast, cervical, ovarian, gynaecologic, lung, stomach, prostate, bladder, gastrointestinal, colorectal, colon, rectal, brain, nonspecific and nonspecific hematopoietic stem cell transplantation), The highest number of studies reviewed have considered whether stage at diagnosis is associated with differences in distance and travel times to healthcare facilities with twelve studies identifying a distance decay effect and seven of them not identifying a statistically significant association (mixed results). The next highest number of studies have considered whether survival following cancer is associated with distances or travel times to healthcare facilities, again there is some mixed results, as whilst the majority present a statistically significant association with poorer outcomes for those travelling further, 19.1% indicate no statistically significant association.

Table 5 Review results by disease group and outcome measure[1]`

Disease	Measure	Decay	Bias	None
Cancer (split into breast, cervical, ovarian, gynaecologic, lung, stomach, prostate, bladder, gastrointestinal, colorectal, colon, rectal, brain, nonspecific and nonspecific hematopoietic stem cell transplantation)	Stage at diagnosis (tumour size, diagnosis at death and emergency presentation)	12		7
	Survival	13	4	4
	Mortality	1	1	1
	Receipt of Radiotherapy	3		1
	Uptake of Radiotherapy	1		1
	Receipt of Chemotherapy	2		
	Receipt of surgical resection (lung)	1		
	Type of treatment received(e.g. breast conserving vs mastectomy, surgery)	7		1
	Time to first treatment	1		1
	Completion of treatment	2		
	Attending screening / adherence to screening guidelines	5		1
	Quality of life	1		
Diabetes	Glycaemic Control	3		
	Foot Ulcers			1
	Amputation			1
Obesity	Gastric Band: Compliance with follow-up	3		
	Gastric Band: Weight Loss	2	1	
Kidney Failure	Mortality	5		
	Visit a nephrologist	2		
	First peritonitis episode			1
	Complications (e.g. infection)	1		
	Quality of Life	1		
	Type of Dialysis (renal replacement therapy)	2		
	Quality Care indicators	1		
	All cause hospitalisation	2		
Transplant (split into Liver, lung , heart, kidney)	Mortality	1		1
	Survival			2
	Being listed	2		1
	Receipt / likelihood of a transplant	1		
	Likelihood of infection			1
	Likelihood of re-transplantation			1
	Quality of life	1		
General Surgery	Length of Stay	2		
	In hospital mortality	1		
	Mortality	1		
	30 day complications	2		
	Readmission	1		
General healthcare	Inpatient episodes	1		
	Primary care attendance/ check ups	2		
Mental Health (split into general and eating disorder)	Attendance	1		1
	Continuity of care	1		
	Seriousness of diagnosis	1		
	Completion of treatment	1		
Asthma	Mortality	1		
Alcohol abuse	Follow up Attendance	1		
Hepatitis C	Detection Rate	1		

[1] The total results by disease differ to the total number of studies (108), as some studies explored more than one outcome or diseaase.

HIV with severe sepsis	In hospital mortality	1		
Tuberculosis	Completion of treatment	1		
Sleep Apnoea	Severity	1		
Pulmonary Arterial Hypertension	Delayed diagnosis			1
AAT deficiency	Delayed diagnosis			1

There is a running theme of patients receiving different treatments based on where they live. For example, patients being less likely to receive renal replacement therapy for kidney disease the further they live away (e.g. Judge et al. (2012b)) or less likely to receive breast conserving treatment and more likely to have a mastectomy the further they live from the hospital (e.g. Schroen et al. (2005). A large number of studies have considered the impact of later stage diagnosis of disease (e.g. Wang et al. (2008a) and increased severity of disease at diagnosis (e.g. Joseph and Boeckh (1981)). Although less in number there are some studies that do not show statistically significant results for either of these associations. The split by disease in table 5 shows that more research is needed in both those areas more commonly studied (e.g. cancer where the evidence is mixed) and the growing range of other diseases, where this association is being considered.

2.4 Discussion

The results were mixed. Eighty three studies identified an association between increasing distance/ travel time and worse health outcomes, nineteen no evidence, and six studies evidence of an association between increasing distance and improvements in health outcomes. Thus the majority of studies reported a negative association between distance and travel time to healthcare facilities and health outcomes. This was true across a multitude of disease groups, geographical distances and boundaries. The wide range of methods, sources of data, disease areas and outcome measures and ranges of distances travelled add to the complexity of the comparisons. The focus of this discussion is on the key differences in the way that the distances and travel times were calculated and analysed and whether there any themes to link an association between distance/ travel time and health outcomes.

2.4.1 Travelling to healthcare

The critical elements of calculating an accurate representation of the distances and travel times that the patients have endured requires a starting location for the journey (e.g. patient home address), end point (healthcare facility) and method for accounting for the estimated route taken between these two points. The included studies differed on all three inputs. Where the

patient's address was unavailable less specific geographical identifiers were used by the studies, ranging from patient's postcode (Lake et al., 2011) zip code centroid (Engelman et al., 2002), centroid of a census district (Judge et al., 2012b) referral hospital (Goldberg et al., 2014), to the centroid of town of residence (Rodkey et al., 1997). A mixture of the methods was used where data was missing at the less aggregated geographical levels (Celaya et al., 2010). Using an origin point that is less accurate than the patient's home address has the potential to reduce the accuracy of the results, as it may influence the route taken affecting the distances and travel times. Though it should be noted that even this location is a proxy as not all patient journeys start from the patient's home address.

The geographical data available for the healthcare facilities attended also differed across studies. Fifty-two percent of the studies had the address of the healthcare facility attended by the patient. The remainder used the address of the nearest facility to the patient, as a proxy. Knowing how realistic the proxy measure is would be a benefit, as it may dramatically change the distances/ travel times calculated. For example, Tracey et al. (2014) identified in their study that only 37% of the patients attended the nearest facility, so using this as the proxy would underestimate the distances travelled by patients.

Studies such as Dejardin et al. (2014) and Bello et al. (2012) identified that where patients were followed up over time - patients had the potential to move home address. It was argued by some studies that grouping distances into large categorical bands allowed patients to move residence, but not actually move categories during the study. In the study by Thompson et al. (2013), 27% of the study's population changed their residence during the 5 year follow up, but 91% of the patients had remained in the original distance category.

The majority of studies focused on one destination (e.g. hospital attended), for one type of treatment (e.g. an operation). This has the potential to underestimate the impact of distance/ travel times on health outcomes – where patients are potentially making multiple trips to a range of hospitals over the course of the year for a range of health issues. In an attempt to be more representative of the travel burden, Brewer et al. (2012) used the follow up radiation centre address as the destination for patients rather than the place they had the surgery, as they argued patients would have to make this journey more frequently. Studies such as Jones et al. (2008b) considered the impact of a range of potential healthcare settings (e.g. distance to the nearest cancer centre, GP, hospital of first referral). They found a significant association between distance and survival for the GP, but not the other healthcare settings studied. Similarly, Wang et al. (2008b) found that as travel times to the nearest GP increased, patients were more

likely to have a later stage breast cancer diagnosis, which was not evident when focusing on the distance to the nearest mammography service. These examples imply that focusing on a single site healthcare location (e.g. hospital where the surgery took place) could miss the location that most influenced the patient health outcomes. The primary referral place for patients with OA and RA as described in Chapter 1 is the GP, so would be important to measure the association to both the GP (as the gate keeper) and hospital.

2.4.2 Measuring distance and travel time

Straight-line distance was used to calculate the distance for >25% of the studies. It is unlikely that any healthcare trip can be made in a straight-line, but it was argued by some studies that grouping distances into categories that covered large geographical areas, can reduce the effects of differences between using road distance and straight-line distance. The remainder of the studies calculated travel time or road network based distance (either shortest route or quickest route). This was calculated in a variety of ways including making use of specific GIS software (e.g. ESRI ArcGIS, MAPINFO, ARCinfo), but more recent papers had used online routing websites such as Google.com (2019), Melissa (2019) or MapQuest (2019). Online resources are straightforward to use and highly accessible to calculate distances and travel times, but there is an ethical question as to whether patient data (e.g. patients home addresses and the hospital attended) should be uploaded to such websites and how secure this is, especially in the case of rarer diseases. A number of studies did take account of the time of year to control for potential differences in the weather and the impact this might have (Celaya et al., 2010), but none included traffic congestion to calculate the travel times, which could significantly have increased the travel times included.

Distances and travel times were included in the statistical models as continuous or categorical variables or both separately. Studies identified that distances / travel times tended to be positively skewed towards more patients living closer to the healthcare facilities that they were attending. In order to better represent this phenomenon Haynes et al. (2008) split the travel times into categories according to the lowest quartile, medium (quartile 2 and 3), high (75^{th} – 95^{th} percentile) and highest (95^{th}– 100^{th} percentile) categories. Other studies linearized distance/ travel time from the natural scale to the log scale, but the majority did not. For studies that included distance/ travel times as a categorical variable there was no consensus on what categories should be used. Study examples include, Sauerzapf et al. (2008) who split the travel distances into < 30 miles, 30 – 60 miles and > 60 miles, Panagopoulou et al. (2012) used

dichotomous categories < 300km and > 300km, Littenberg et al. (2006) split data into < 10 km and ≥ 10 km and Allen et al. (2016) calculated the mean distance and used this to split the data into two groups. Other studies used quartiles or quintiles. In many cases no justification was given for how the categories were determined, which has the potential to hide effects, where critical thresholds are missed. What the studies did identify was that the results were sensitive to the cut offs used in the model. Athas et al. (1999) found that after adjusting for age the likelihood of receiving radiotherapy following breast conserving surgery decreased significantly with increasing travel distance to the nearest facility for distances >74.9miles compared to <10miles, but not for categories in-between. In this case a dichotomous threshold that compared < 30 and ≥ 30 might not have picked up this effect. Undertaking a sensitivity analysis around the reference distance groups and categories used in models would be advantageous– as this may greatly influence the results. Abou-Nassar et al. (2012) and Maheswaran et al. (2006) presented results from the model that treated distance as a continuous variable, the results were not statistically significant for the models that they had tested using categories.

This systematic review was designed to reduce some of the heterogeneity in the studies by focusing on studies completed in global north countries, as they were more likely to have similar healthcare provision and transport networks to get patients to the healthcare facilities. Whilst this has reduced some of the heterogeneity it does not completely remove all of it. There are still differences between the studies in how the healthcare is provided and in the distances that some patients have to travel in some of the studies to access healthcare within these countries (among other things). For example, focusing on colorectal cancer survival, Cramb et al. (2012) grouped patients into the travel time bands of < 2 hours, 2- 6 hours and > 6 hours of travel time, which is very different to the travels times to the healthcare facility recorded for the study by Dejardin et al. (2014), using the categories of 0 – 5 mins, 6- 20 mins, 21-40 mins, 41-90mins and ≥91 mins. All of which would have fitted into the first category (<2 hours) of Cramb et al (2012). These are the key reasons why the results were not pooled in a meta-analysis. The results should be interpreted as answering the research question - Does it show any association between travelling further and having worse health outcomes?, but alongside being aware that the different studies as shown in tables 2 – 5 may have differences in the scales of distances and travel times to the healthcare facilities in the study.

2.4.3 Mode of transport

It was assumed in the majority of studies that patients would travel by car although there were exceptions (e.g. Skarsvag and Wynn. (2004), Arcury et al. (2005), Moist et al., (2008)). For some

patients (potentially in the most deprived groups) it will not be possible to access healthcare by car. Moist et al. (2008) reported that increased public transport travel time for patients contributed to missed kidney dialysis sessions. Jennings et al. (2013) reported that public transport travel times were longer for patients who did not attend follow up appointments compared to those that did. Other studies included public transport access through proxy measures (e.g. whether patients were within 800m walking distance of an hourly bus service). Issues with this include that it does not account for whether the bus service identified goes to the hospital, the travel time once on the bus or the likelihood of the patient being able to walk 800m. In one study, a travel survey of patients' trips to the hospital found that 87% were made by car (Crawford et al., 2009). To ensure representative travel times/ distance it is critical to understand the patient population (in this case how they are travelling).

2.4.4 Key Relationships

The studies in the review highlight some of key factors that were found to be more sensitive to the distance decay effect. For example, Joseph and Boeckh (1981) identified that the distance decay effect was more pronounced for less serious illnesses and Arcury et al. (2005) that patients attended more regular check-up care visits the shorter the distance to the facility. Whilst for Lara et al. (2005) distance was a predictive factor for not attending *in-between* follow up appointments (at 6 and 9 months), whereas it was not predictive for the 12 month or 3 month follow up appointments following a gastric band being fitted. These studies all suggest that when patients feel the health situation is more serious or they live closer they are more likely to attend. In their study Abou-Nassar et al. (2012) found that the impact of distance on health outcomes was only statistically significant 1 year after a transplant suggesting that the point at which the health outcome and distance is measured could be critical to the results. Lake et al. (2011) identified that whilst there was an effect of distance on patients attending treatment for tuberculosis, when doing sub-group analysis this was only statistically significant for those patients not native to the country, so potentially identifying an impact of reduced ability to travel for patients who are less familiar with the healthcare system and transport network. All of which could be considered when tailoring healthcare provision and require further research.

One of the key influencing variables identified by the studies was deprivation. Dejardin et al. (2014) found that when controlling for deprivation the effect of distance on health outcomes was removed, whilst Crawford et al. (2009) that distance amplified the effect from deprivation. From one side it might be argued that by controlling for deprivation this is also removing some of the impact of distance/ time that is experienced by those who do not have access to a car and

would have to travel by other means. Those studies in the review not controlling for deprivation may be overestimating the true impact of distance travelled/ travel time on patients' health.

Studies such as those in Table 3 indicate that in some cases patients are able to travel longer distances and have better health outcomes than those living closer. This indicates that there are factors other than distance (such as deprivation) that contribute to how easily patients can travel to access the healthcare facilities. Differences in distances that patients would be willing to travel (travel thresholds) to primary care practice have been explored in studies such as McGrail et al. (2015) who asked patients "*What is the maximum time (minutes) you are prepared to travel to see a GP (for something that wasn't an emergency)?"* (p 3). Communities where the population was sparsely located were found to be willing to travel a maximum of 22.2 minutes more to visit the primary care practice than those in closely settled communities. Buzza et al. (2011) found that distance was the most important barrier to accessing healthcare in their study, but also identified "*health status, functional impairment, travel costs and work or family obligation*" as key barriers (p648). Similarly the Social Exclusion Unit in the UK proposed that a person's ability to travel was influenced by key factors including their *Travel Horizons* (Where are they willing to travel to? What is the maximum distance they are willing to travel? And do they have full awareness of available transport options for the journey), *Cost* (Can they afford to travel to the healthcare facility?), *Physical Access* (their health state may make accessing transport physically difficult or if accessing public transport there may not be an appropriate route) and *Crime* (they may not want to travel unless they felt safe making the journey) (Social Exclusion Unit, 2003). All these factors need to be considered when deciding on where to locate a healthcare facility / improve access for patients to an existing facility and ultimately improve health outcomes. For studies such as Bristow et al. (2015) closer investigation of those patients living <5km from the hospital whose health outcomes were worse than those living further away, or in the case of Kim et al. (2000) what makes those patients living 20 – 30 km away have better health outcomes – what makes them different? And how can these other groups be better supported to access healthcare services? Using the types of studies brought together in this review allows some of these questions to be explored and inform debate over potential solutions.

The reason for undertaking this review was to collate and review evidence on the potential impact of distance and travel time to healthcare on patients' health outcomes. This is particularly pertinent given the move to centralised specialist services which typically means increased travel distance to access those healthcare facilities. Studies such as Kerschbaumer et

al. (2012) have shown that if follow up can be completed successfully at a local level (even if the surgery is centralised) this can improve health outcomes and reduce travel burden. The review has shown that by making use of ex-post healthcare data, providers can identify spatially pockets of patients who would be disadvantaged through having to travel further to access healthcare facilities and could use this to examine how these patients match with existing support and transport networks. It has also shown that it is not just about identifying patients who have to travel the furthest with evidence of patients living in close proximity to the healthcare facilities often fairing the worst. More research is needed to pick up on these factors and to explore in more detail the impact that the methods and data sources have on the results.

2.4.5 Strengths and Limitations

This systematic review has for the first time synthesised available evidence on the association between differences in travel time/distance to healthcare services and patients' health outcomes. It identified a wealth of studies and generated evidence for a wide range of disease groups and health outcomes, across multiple countries. There was great variation in study design, distances and travel times to the healthcare setting, and range of health outcomes; this precluded pooling of data for meta-analysis. The study followed a search strategy to maximise the identification of relevant studies of which 19 did not find an association between distance/ travel time and health outcomes; this is likely to be an underrepresentation if authors have a tendency to not publish results that showed no effect. While the review findings are of undoubted value in broadening our understanding of the wider societal factors that influence health outcomes, their applicability may be limited to countries with similar healthcare systems. The studies in this review were limited to Global North countries.

2.5 Conclusions

The majority of studies (77%) showed evidence of an association between worse health outcomes the further a patient lived from the healthcare facilities they needed to attend. This was evident at all levels of geography – local level, interurban and inter-country level. A distance decay effect cannot be ruled out and distance/ travel time should be a consideration when configuring the location of healthcare facilities and treatment options for patients. None of the included studies focused on an OA/RA patient group, which is the focus of this thesis, but did identify valuable key findings. The key findings taken forward in the remaining chapters of this thesis are:

- The statistical models used in the studies showed differences when including travel times/ distances, as continuous and categorical variables. It is important to consider both, as the

thresholds used in the categories might highlight differences that are not apparent as a continuous variable. The studies used a range of methods (e.g. straight - line distance and road network distance) and it will be important to assess whether there are any statistically significant differences in these different approaches.

- The studies used a range of more and less specific patient home locations (postcode, wider geographical area)
- The studies used a range of more or less specific healthcare locations (nearest/ actual facility attended). It will be important to assess whether the nearest facility is equal to the actual facility attended and whether the nearest is a suitable proxy for the hospital attended. This will be considered in Chapter 3, as Chapter 4 relies on nearest facilities, as the destination point.
- A number of the studies that focused on a range of healthcare destinations found that distance/ travel time to the GP (as the gatekeeper to healthcare treatment) had a statistically significant association with health outcomes. It is therefore important not to focus just on one point of healthcare access.
- Assuming that patients have travelled to healthcare facilities by car may underestimate the distances and travel times that some patients will have to travel. It is also important to take account of key variables including deprivation and comorbidities in the statistical models, as identified in a number of the included studies.

This chapter has focused on bringing together the evidence on the association between travel time and distance to healthcare and health outcomes. None of the included studies in the systematic review focused on OA or RA as a disease group. The next chapter describes the first case study focusing on whether travel times and distances are associated with differences in health outcomes for OA patients who have undergone a total hip or knee replacement in West Yorkshire.

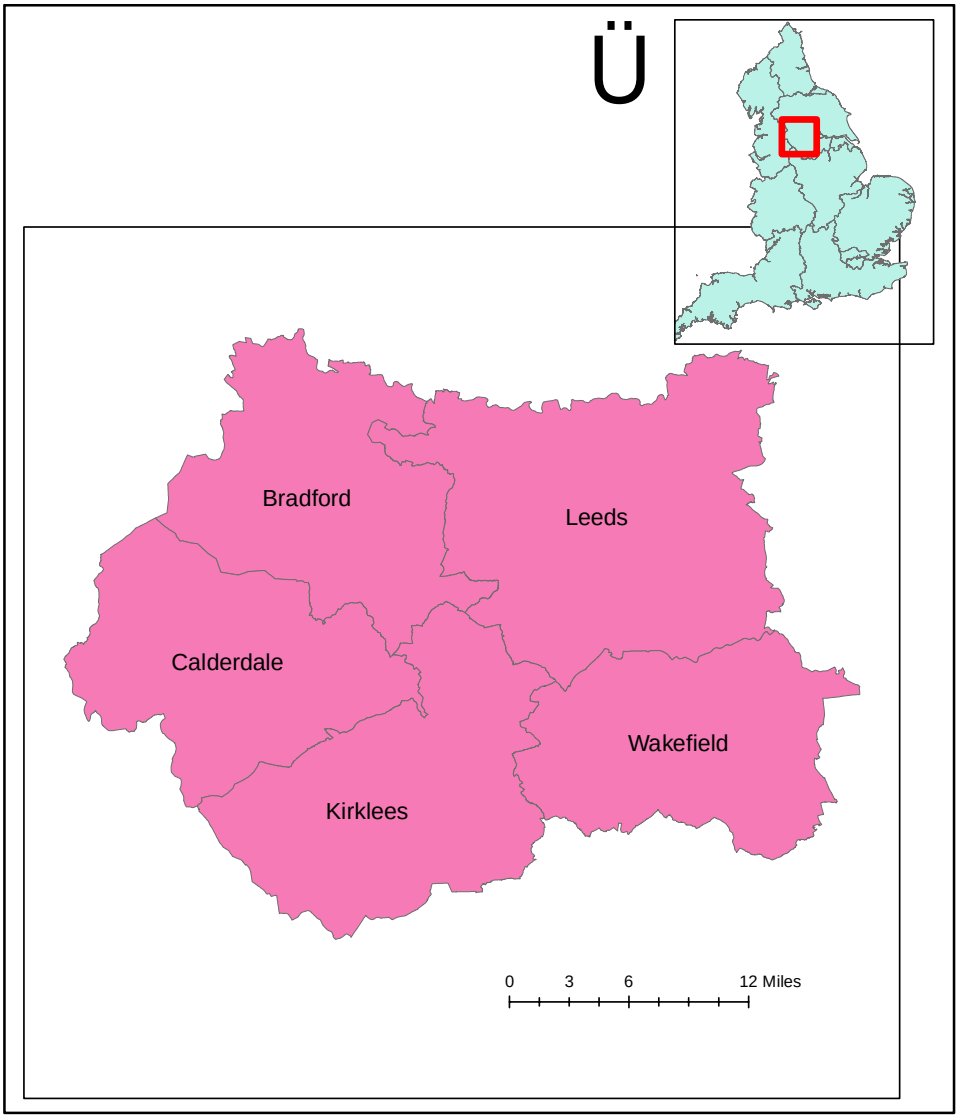
3 Chapter 3: West Yorkshire Case Study: Measuring the association between transport accessibility and health outcomes

3.1 Introduction

Chapter 2 of this thesis reported on the systematic review that assimilated evidence on studies that had considered the association between health outcomes for patients and living further (measured using travel times or travel distances) from the healthcare facilities that they needed to attend. This Chapter takes this evidence forward and explores the associations between travel time and distance to healthcare facilities (e.g. GP and hospital) and differences in health outcomes for total hip replacement (THR) and total knee replacement (TKR) patients in West Yorkshire (WY), England. It has been designed to contribute to the following study objectives:

> *Objective 2: To explore and document the healthcare and transport accessibility needs of patients with osteoarthritis and rheumatoid arthritis.*
>
> *Objective 3: Develop statistical models to examine the associations between transport accessibility to healthcare and inequalities in health for individuals diagnosed with RA and OA. For two case studies:*
>
> - *Case Study 1: West Yorkshire. Using the linked Hospital Episode Statistics – Patient Reported Outcome Measures (HES-PROMS) dataset*

West Yorkshire is a Metropolitan county with a population of over 2.2 million spread across five districts; Leeds, Bradford, Calderdale, Kirklees and Wakefield (shown in Map 1). Data was accessed for 2009/10 – 2011/12, which falls into the period of time when healthcare was organised into Strategic Health Authorities (SHA) and Primary Care Trusts (PCTs), which were abolished in March 2013 in favour of Clinical Commissioning Groups (CCGs). West Yorkshire was under the NHS Yorkshire and Humberside SHA and five PCTs; NHS Calderdale PCT, NHS Kirklees PCT, NHS Wakefield District PCT, NHS Bradford and Airedale Teaching PCT and NHS Leeds PCT. Whilst healthcare delivery was organised geographically into PCTs, following changes to the NHS constitution in April 2009 patients had the right to choose (from hospitals that treat NHS patients in England) where to have their THR or TKR operation (Department of Health, 2009).



Map 1: Location of West Yorkshire in England (source: ONS: 2011)

3.1.1 The HES-PROMS dataset

The study accessed the linked Hospital Episode Statistics (HES) and Patient Reported Outcome Measures (PROMS) dataset to explore the research question for this Chapter. The HES dataset contains key information for every NHS outpatient, inpatient and Accident and Emergency (A & E) appointment or visit for patients in England. Every time a person goes into hospital information is recorded by the hospital on things including their age, gender, any diseases that they have (e.g. osteoarthritis) and their home postcode. Plus information about who their appointment was with (e.g. type of consultant) and the treatment they received (e.g. total hip replacement). The dataset is held by NHS Digital (previously called the Health and Social Care Information Centre (HSCIC)). Since 2009 this dataset has been linked to the PROMS dataset,

which collects data including quality of life data before and after patients undergo operations for THR or TKR, varicose vein removal or hernia repair. Patients are given a questionnaire to complete before the operation and a second questionnaire is sent out to patient's homes six months after the operation to be completed and returned. One of the key advantages of using this dataset is that it provides linked health outcome and patient data for patients that could be identified from the records as having either OA or RA. The data requested from the HSCIC for the study (summarised in Box 1), includes all outpatient, inpatient and A & E data on the patients with OA/RA who accessed a WY hospital between April 2009 and March 2012.

Box 1 Population data request for HES-PROMS dataset.

Stage 1:

- Patients who attended at least one West Yorkshire or Harrogate (outpatient or inpatient hospital appointment) between April 2009 and March 2012 (provider codes - NT225, NT332, NT348, NT349, NT350, NT447, NT448, NVC20, RAE, RCD, RCF, RGD, RR8, RWY, RXF-X, TAD) AND
- Had an International Classification of Diseases Version 10 (WHO, 2016) code for Osteoarthritis (M13, M15, M16, M17, M18, M19, M47) or Rheumatoid Arthritis (M05, M06, M45) or the treatment speciality code recorded as rheumatology AND
- Were > 17 year old.

Stage 2:

For those patients identified in Stage 1 the study requested all data (A & E, Outpatient, Inpatient and PROMS) linked to these patients for the years requested.

In order to correctly identify those patients with OA or RA the International Classification of diseases version 10 (WHO, 2016) was searched to select those specific codes that are entered by the hospital into the dataset for each patient's inpatient episode that identifies them as having OA or RA. It should be noted that this classification is not always entered against the patient's record for the outpatient appointments or A & E attendances, but is required for inpatient stays, due to associations with entering the data and reimbursement of costs for the hospitals. The hospitals cannot claim the costs if the data is not entered. There are seven codes specifically for OA:

- M13 = Other arthritis
- M15 = Polyosteoarthritis
- M16 = Osteoarthritis of hip
- M17 = Osteoarthritis of knee
- M18 = Osteoarthritis of first carpometacarpal Joint
- M19 = Other and unspecified osteoarthritis
- M47 = Osteoarthritis in the spine

There are three code specifically for RA:

- M05 = Rheumatoid arthritis with rheumatoid factor
- M06 = Other rheumatoid arthritis
- M45 = Ankylosing spondylitis (in the spine)

In order to identify only those patients who had attended a hospital in West Yorkshire in the given timeframe the hospital provider codes were collated. For example, hospital provider code NT225 in box 1 refers to the Nuffield Health, Leeds Hospital and RR8 refers to all the hospitals within Leeds Teaching Hospital NHS Trust.

The key variables requested from the HES-PROMS dataset are summarised in Table 6. Data was requested on inpatient stays, outpatient appointments and A & E visits at the patient level. Only the inpatient stays and outpatient appointments were subsequently used in the analysis. This was due to the study narrowing the focus onto the THR and TKR operations rather than the patient's visits to the A & E. The data was accessed at the patient level, which means that for every A & E visit and outpatient appointment there is a record for each patient. For the inpatient appointments the data is provided at the episode level. An episode is the time a patient spends under the continuous care of one consultant. If the patient as a result of their treatment transfers during their time in hospital to more than one consultant then there would be more than one episode recorded across a multiple episode stay for that patient for their inpatient stay. Whilst some of the variables for a patients stay in hospital will remain the same (e.g. age, gender) others might change including the consultant type and the hospital attended if a transfer between hospitals had been required.

At the time of this study taking place it was not possible to link primary care data (which is collected through a separate system) to the HES-PROMS dataset. This is still not possible (at the time of this thesis being submitted). As noted in Chapter 1 access to the GP is one of the main ways that patients with OA are treated and was also identified as a key access point in some of the studies included in the review in Chapter 2. The patients' registered GP practice was included in the request to take some account of this in the analysis.

Table 6: Summary of main variables requested from HES and PROMS

Patient	Month and Year of Birth Ethnic Category HES patient identifier Gender
Variables based on where the patient lives	Home Address (postcode) Census output area 2001 LSOA (Lower Layer Super Output Area) Rural/ Urban indicator Index of Multiple Deprivation
Healthcare facility Attended	GP practice Hospital provider (location of treatment/ appointment)
Procedures/ diagnosis (only routinely recorded for inpatient appointments)	Dominant procedure All diagnosis codes All operation codes Treatment specialty of consultant
Appointments/ Hospital stays	Dates of attendance at hospital Length of stay (for inpatient appointments only) Missed Appointments Discharge method Whether the patient died in hospital. Time of attendance (for A & E appointments only)
PROMS	EQ-5D-3L EQ-5D VAS General Health Assessment Oxford Hip Score (OHS) Oxford Knee Score (OKS) Living Arrangements

The study applied for home postcode data to allow distance and travel times (home to healthcare facility) to be calculated. An added complication of this was that by applying for the home postcode variable (classed as patient confidential) there was a requirement to get a higher level of ethical approval than for the standard HES-PROMS applications. An alternative

geographical identifier that would not have required approval at this level is the Lower Super Output Area (LSOA), which can provide a location (using the population weighted centroid for the LSOA) based on groups of 400 - 1200 households, but is potentially less accurate than the home postcode, which is representative of between 2 and 80 households. The study used both types of geographical locations (home postcode and LSOA) in the calculations to assess whether there were any statistically significant differences between the results.

3.1.1.1 Ethical Approval for the HES-PROMS data

The study went through multiple ethical approval stages to gain access to the data required. An NHS Integrated Research Application System (IRAS) application was populated with information including the study protocol, the study population, the data security procedures and policies. This was reviewed by the Faculty of Medicine Ethics within the University of Leeds before being submitted to the NHS Health Research Authority (HRA) Research Ethics Committee (REC) for review and approval. The proposal went before the Leeds East Committee in December 2014 and was granted approval on the 4th of December 2014 (reference 14/YH/1262). As the study was requesting access to data at the level of the patients' home postcode there was a requirement to submit the forms and additional information to the HRA Confidentiality Advisory Group (CAG). Patient home postcode data is classed as *patient confidential,* which requires either the permission of the patients whose data has been included or alternatively Section 251 approval, which allows the use of the data without individual patient permission, subject to meeting eligibility criteria. The study was granted Section 251 approval in April 2015 from CAG (ref: 15/cag/0001). The final stage was to request the data from the then Health and Social Care Information Centre (HSCIC) (now NHS Digital). Approval was granted in September 2015 and the data was received in December 2015. The HRA and HRA CAG approval both require submission of an annual report to maintain access to the data (updating the organisations on how the data is being used). The NHS Digital data sharing agreement required an annual renewal. The process of obtaining the data was a long and arduous one. Key issues included that the HSCIC had imposed a blanket ban on releasing HES data, which was only lifted just before the study requested the data. The process for applying had new procedures including new considerations for the fair processing of data that were still being determined during the application. The data was stored on a secure drive accessible only through the computer at the University. This met the NHS requirements for holding data securely.

3.1.2 The Patients: THR and TKR

As described in Chapter 1 surgery in the form of joint replacements is one of the options on the care pathway for patients with OA or RA. Two of these possible operations that are completed to ease pain, improve mobility and improve sleep are the TKR and THR. The THR involves a total joint replacement, which is the replacement of the femoral head with a stemmed femoral prosthesis and the insertion of an acetabular cup, which can be completed with and without cement. The TKR involves replacing both sides of the knee joint. The end of the femur replaced by a curved piece of metal, and the end of the tibia replaced by a flat metal plate. A plastic spacer is placed between the pieces of metal to reduce the friction as the joint moves. THR is a common surgery with over 105,000 taking place across England, Wales and Northern Ireland in 2017 (National Joint Registry, 2017). There were more TKRs at over 114,000 in the same timeframe (National Joint Registry, 2017). The operations are designed to replace joints worn by age or damaged by conditions such as arthritis. For THR operations patients undergo either a cemented hip replacement, which involves a layer of bone cement between the patient's bone and prosthesis, or uncemented where the prosthesis has a rough surface or porous coating that encourages the natural bone to grow onto it. The review by Abdulkarin et al. (2013) comparing the two options (cemented and uncemented) concluded that there were *"no significant differences in the revision rate, mortality or the complication rate"* (p 1), but that patients reported improved HRQoL for pain under the cemented THR. For a TKR operation the damaged cartilage and bone is removed and metal implants are attached to the thigh and calf bones with a plastic spacer inserted in-between to ease movement.

As part of the process for deciding where patients attend for their operation, information is provided to the patients through the NHS Choices website (NHS, 2017) on how to make the choice over where to have the operation. The information includes distance to the hospital, waiting times, number of parking spaces, number of hip revisions completed at the hospital, and HRQoL scores for previous patients.

Having a diagnosis of OA or RA in the hip or knee does not automatically qualify an individual to have a THR or TKR. As discussed in Chapter 1 some individuals have radiographic evidence of OA in their joints, but do not experience the severe pain and others have pain or a symptomatic diagnosis, but no radiographic evidence. As shown in Figure 4 and 6 there are other approaches (e.g. exercise, diet, pain killing injections such as corticosteroids) that are promoted before an individual is considered for a THR or TKR. In England the criteria for allowing an individual to

have a TKR or a THR is set by the individual CCGs, as it is not a routinely funded surgery. It is a NHS clinician's decision to decide whether the individual meets the required threshold for a THR or TKR. An example of the key requirement for THR and TKR for OA from Harrogate and Rural District CCG (2014) states that it will be commissioned if the :

- *"Patient is experiencing moderate-to-severe persistent pain not adequately relieved by an extended course of non-surgical management. Pain is at a level at which it interferes with activities of daily living – washing, dressing, lifestyle and sleep;*
- *Is troubled by clinically significant functional limitation resulting in diminished quality of life;*
- *The patient is fit for surgery with a BMI ≤35 and a non-smoker. Patients with a BMI >35 and/or who smoke should be advised and given appropriate support to address lifestyle factors that would improve their fitness for surgery. … a clinician should confirm that reasonable attempts have been made to stop if still a smoker.*
- *The patient has radiological features of disease.*
- *A simple x-ray to confirm diagnosis has been carried out within the past 6 months"* (p1)

The study focused on TKR and THR as they both form one of the possible treatments on the care pathway for patients with OA and RA. In addition, critically linked data was collected at the individual patient level through the PROMS dataset for patients having these two operations, so providing linked treatment, location and health outcome data for the patients. Other operations that are also carried out for patients with OA or RA such as shoulder replacements could be identified in the HES dataset, but did not have the corresponding patient health outcome data. An alternative dataset that was considered is the National Joint Registry (NJR), which collects information on hip, knee, ankle, elbow and shoulder joint replacement surgery and monitors the performance of joint replacement implants. At the time of applying for data for this study it was not possible to get access to elbow, shoulder or ankle data for the timeframe that was being considered (they have been collected from later dates than hip and knee.). The NJR collects more detailed information on the specifics involved in the operations than HES including the surgeon's details, operation details (e.g. anaesthetics used) and surgical approach and collects the patients BMI, but does not collect data on the patient's ethnicity or registered GP or record any other hospital appointments other than the TKR or THR. One of the limitations of the NJR is that unlike the HES dataset (where hospitals are required to enter the patient data onto the system) patients have to give permission for their personal details to be held by the database. In 2009/10, one of the years being considered in this study only 87.5% of the

submitted forms to the NJR had consent to be included (so were missing from the NJR dataset) and some of the NHS hospitals had not submitted any forms , so were not included in the dataset (which is only mandatory for independent sector hospitals) (NJR, 2010)(p22). The decision was made to apply for the HES-PROMS dataset in 2014 as it allowed access to data on all appointments (inpatient, outpatient and A& E) that were attended by the patients for the THR and TKR not just those, where the hospitals had submitted the data and the patients had consented to the data being used by researchers. Plus is allowed access to code of the patients registered GP to allow this aspect to be explored. New rules have since been introduced for the HES data to ensure that patients who want to opt out of having their data used for research purposes will not be available in the datasets given out to researcher (an opt out rather than opt in). This rule was not applied to the data used for this study, so all data was included and there were no missing patients.

3.1.3 Health Outcome Measures

Measuring health outcomes is important as whilst studies have shown that THR and TKR procedures reduce the symptoms in the majority of patients and the operation is associated with low rates of complications and mortality there are still a proportion of patients reporting unfavourable outcomes. A systematic review by Beswick et al. (2012) concluded that "*The proportion of people with an unfavourable long-term pain outcome in studies ranged from about 7% to 23% after hip and 10% to 34% after TKR. In the best quality studies, an unfavourable pain outcome was reported in 9% or more of patients after hip and about 20% of patients after knee replacement"* (p 1). A review of the literature identified a plethora of measures that had been developed and used to assess health outcomes following THR and TKR operations. The most commonly used measures in the literature are summarized in Appendix 2 including an assessment of whether they are a generic measure, or disease specific and who makes the assessment (patient or clinician). The literature represents a mixture of measures that are assessed by clinicians, patients self-reported assessments of their health and quality of life and objective measures (e.g., mortality). These include generic health measures such as the EQ-5D-3L and SF36 , which were designed to measure a patient's health, but were not disease specific - to disease and joint specific measures for assessing the hip such as the Oxford Hip Score (OHS) ,Harris Hip Score(HHS), Hip Outcome Score (HOS), Western Ontario and McMaster Universities Arthritis Index (WOMAC), HiP Disability and Osteoarthritis Score (HOOS) and Lower Extremity Functional Scale (LEFS) and for the knee including the Knee Society Score (KSS), Knee disability and Osteoarthritis Outcome Score (KOOS) and Oxford Knee Score (OKS). Added to this

are objective measures such as mortality, and joint failures and functional ability assessed by clinicians using measures such as the six minute walk test (6 mWT) and Timed Up and Go test (TUG).

A number of these measures are included in the PROMS questions that patients complete before and six months after their THR or TKR operation in England. The most commonly used are the generic EQ-5D-3L and EQ-5D VAS, which form the basis of the health related quality of life scores (The EuroQol Group, 1990), Self-Reported General health, and disease specific Oxford hip score (OHS) (Dawson et al., 1996) and Oxford Knee Scores (OKS) (Dawson et al., 1998). A number of studies have compared the performance of these measures for THR and TKR patients (e.g. Benson et al. (2016) and Oppe et al. (2011)). With Benson et al. (2016) defining the OHS and OKS as the Gold Standard measure for THR and TKR.

As discussed in Chapter 1 there are a number of potential determinants that can potentially affect a patient's health. A growing number of studies have sought to identify key patient predictors for patients undergoing THR and TKR operations. Buirs et al. (2016) systematic review of predictors of physical functioning after a THR identified 33 relevant studies focusing on predictors, which used the following health outcome measures; HHS. OHS, SF36, LEFS, TUG and WOMAC. They reported that there was strong evidence for an association between BMI, age, comorbidities, preoperative physical function and mental health with functional outcomes following the THR, but only weak or inconsistent evidence for education, gender and socioeconomic status. Gordon et al. (2014) used a large Swedish cohort of THR patients and showed that there were worse outcomes for older people (they achieved less improvement following the operation). Fitzgerald et al. (2004) followed 222 patients for 12 months following their THR or TKR operation and identified that following the operation lower pain levels were associated with being over the age of 75 years, having greater social support (e.g. not living alone), undergoing a THR rather than TKR and having less pre- operation body pain. Being male, having greater social support and higher pre-operative scores were associated with better quality of life outcomes in terms of physical function (ibid). McHugh et al. (2013) followed 206 THR patients in England and identified that patients with anxiety and depression prior to the operation were associated with poorer recovery outcomes following the operation.

Not all the evidence currently points to a strong association between predictive factors and health outcomes/ proxy measures. Hofstede et al. (2016) identified 35 studies covering the health outcomes and proxy measures of SF36, EQ-5D-3L, SF12, WOMAC, OHS, HHS, HOOS, Pain, Satisfaction, 6 mWT and revisions that had focusing on studies focusing on the association

between age, gender, education/SES, comorbidities, BMI, radiology severity, patient expectations, and pre- operation function, pre-operation pain, pre –operation HRQoL and mental health and outcomes following a THR. They concluded that currently *"there was not enough evidence to draw succinct conclusions on pre-operative predictors for postoperative outcome in THR, as results of studies are conflicting and the methodological quality is low*" (p9). Towheed and Hotchberg (1996) argued that future research in this area should focus on "*patient level predictors and the role of various surgical approaches"* (p483). Judge et al. (2012a) also focused on identifying pre-operation predictors of health outcomes following knee surgery and found that patients reported worse outcomes if they had more severe disease prior to the operation, had OA compared to RA and lived in the most deprived areas. They concluded that *"other predictive factors need to be identified to improve our ability to recognize patients at risk of poor outcomes" (p1804).* One of these "other predictive factors" could be living further from the hospital, or GP for this group of patients, as patients need to attend the GP in the first place to be referred into the system to be considered for a THR or TKR. There is a need to attend hospital for the pre-operative appointments (including to have x-rays), operation and then follow up appointments. This could lead to an increased travel burden over time given that the majority of patients have to travel to healthcare facilities to attend appointments and receive treatment. The patient level predictive factors that have been investigated in the literature has focused on the association between age, gender, BMI, education/ SES, comorbidities, alcohol consumption,, allergies, deprivation, living alone, pre-operation radiology severity, pre-operation function and pain, pre-operation HRQoL, mental health and post operation health outcomes and time on the waiting list. None of the studies have focused on the association between transport accessibility and health outcomes for TKR and THR, which is the focus of this thesis.

Length of Stay (LoS) in hospital and missed appointments have also been considered in the literature. Studies such as Jackson et al. (2013) found an association between living further from the hospital and an increased LoS, as a proxy outcome measure for health outcome. Whilst Hamilton and Gourlay (2002) in their report on missed appointments argue that *"there is a strong link between transport and nonattendance of hospital appointments"* (p32). They also argue that there is little research in this area, which falls between the responsibility of the Department of Health and Department of Transport and is not considered a priority by either. Missing appointments can result in delays in diagnosis and treatment.

The review in Chapter 2 did not identify any studies that had explored whether travel times or distances to healthcare facilities were associated with changes in health outcomes either for patients with arthritis or after having a THR or TKR, which will be the focus of this chapter. Preliminary investigation of the data found that there were only 50 patients with RA that had had a THR/TKR in the timeframe of the data. A decision was made at this point due to the small numbers to focus this Chapter on those patients with a OA diagnosis on their hospital records who had had a TKR or THR.

3.2 Methods

Once the study had access to the data and had stored it securely in the University's encrypted drive there were a number of stages to the process for analysing the data. These focus on:

Section 3.2.1: Dependent Variable: Health Outcomes

Section 3.2.2: Dealing with missing health outcome data

Section 3.2.3 Independent Variable: Travel time and distances to the healthcare facilities

Section 3.2.4: Other Explanatory / Predictor Variables

3.2.1 Dependent Variable: Health Outcomes

The key aim is to model the association between the travel times and distances to healthcare facilities and the dependent variable which is the health outcome or proxy health outcome. The study makes use of the health outcomes that were included in the PROMS survey completed by the patients at baseline (pre operation) and 6 months following the operation. These outcomes measures were the OHS, OKS, EQ-5D-3L, EQ-5D VAS and General Health. The OHS, OKS and EQ-5D-3L have previously be applied in studies that have focused on patients who have had a TKR or THR (as discussed in section 3.1). In addition to this the study included the proxy measure of LoS in hospital (days) following the operation and attendance at outpatient appointments, which were both accessed just from the HES data for this population of patients. A summary of the measures are provided in Table 7 and description in the next section.

Table 7: Health and Proxy Health Measures

Dataset	Measure	Use	Range/ scale
PROMS	EQ-5D-3L	Generic	- 0.594 – 1.0
	EQ-5D VAS	Generic	0 - 100
	General Health	Generic	Excellent, Very Good, Good, Fair, Poor
	Oxford Hip Score	THR	0 – 48
	Oxford Knee Score	TKR	0 – 48
HES	Length of Stay	Generic	Days
	DNA	Generic	Attended/ did not attend an outpatient appointment

3.2.1.1.1 EQ-5D-3L

The EQ-5D-3L was developed by the EuroQoL group as a generic measure of self-assessed health to be applied to a range of conditions (The EuroQol Group, 1990). It consists of 5 dimensions of; mobility, self-care, usual activities, pain/discomfort and anxiety/depression, as shown in Figure 8. Patients are asked to state whether they have no problems (scored 1), some problems (scored 2), or extreme problems (scored 3) against each of the 5 dimensions. This is converted into a self-assessed health state of 11111 if they have no problems on any of the domains and 33333 if they have extreme problems for each of the 5 domains, with a total possible 243 health states. Health states are assigned an index score between -0.549 and 1 by applying the UK population preference weights (tariffs) taken from (Dolan, 1997). Where 1 is bounded as full health and 0 as death. Values below 0 are classed as states worse than death.

By placing a tick in one box in each group below, please indicate which statements best describe your own health state today.

Mobility

I have no problems in walking about ☐

I have some problems in walking about ☐

I am confined to bed ☐

Self-Care

I have no problems with self-care ☐

I have some problems washing or dressing myself ☐

I am unable to wash or dress myself ☐

Usual Activities (*e.g. work, study, housework, family or leisure activities)*

I have no problems with performing my usual activities ☐

I have some problems with performing my usual activities ☐

I am unable to perform my usual activities ☐

Pain/Discomfort

I have no pain or discomfort ☐

I have moderate pain or discomfort ☐

I have extreme pain or discomfort ☐

Anxiety/Depression

I am not anxious or depressed ☐

I am moderately anxious or depressed ☐

I am extremely anxious or depressed ☐

Figure 8: EQ-5D-3L Domains Source: (The EuroQol Group, 1990)

3.2.1.1.2 EQ-5D VAS

The EQ-5D VAS (visual analogue scale) was designed to be used alongside the EQ-5D-3L (The EuroQol Group, 1990). Whereas the EQ-5D-3L splits the health of a patient into a number of pre-specified domains the EQ-5D VAS allows patients to make an assessment of their overall health. Patients indicate on the scale shown in Figure 9 how good or bad their health state is on the day they completed the survey. This point on the scale represented as a value between 0 and 100 can be analysed as a quantitative measure.

Figure 9: EQ-5D VAS Source: (The EuroQol Group, 1990)

3.2.1.1.3 General Health

The next measure of health is the Self-Assessed General Health. This is the only measure of health that is also included in the ELSA dataset used in Chapter 4. It is presumed that when answering the question "*In general would you say your health is?* " that multiple facets of health are being considered by the individual. This questionnaire has been applied in numerous settings and forms one of the questions in the UK 10 yearly census. For example, in the 2011 census 81.4% of people in England reported their general health as either 'Very Good' or 'Good' (ONS, 2016a). The general health question in the PROMS dataset is completed before and after the operation and asks patients:

In general would you say your health is? Excellent, Very Good, Good, Fair, Poor.

3.2.1.1.4 Oxford Hip Score (OHS) and Oxford Knee Score (OKS)

The three previous measures discussed (EQ-5D-3L, EQ-5D VAS and Self Assessed General Health) are all generic measures and can be applied to a range of disease groups to assess HRQoL. The Oxford Hip Score (OHS) and the Oxford Knee Score (OKS) were developed to provide PROMS for joint replacements specifically for the knee and hip (Dawson et al., 1996; Dawson et al., 1998). These two measures are described in Benson et al. (2016) as the gold standard measure for capturing the results of THR and TKR. The questionnaire in each case has 12 questions, which relate to the previous 4 weeks of the patient life, so is not just based on how the patient feels on the day they complete the questions. This differs from measures such as the EQ-5D VAS, which asks about the patients' health on the day that they complete the questions. An example showing the OHS (questions used for the THR patients) is shown in table 8. Each question is scored between 0 and 4, with a 4 indicating no problems. These scores are combined to give a total score between 0 and 48. Where 0 is the worst possible score and 48 the best. It covers a wider range of questions than the previous measures. For example, instead of asking whether they have no/ some or extreme problems in mobility, as in the EQ-5D-3L measure there are a range of questions that are specific to the hip problem (e.g. "*Have you had trouble washing and drying yourself (all over) because of your hip? ").*

Table 8: Oxford Hip Score questions. During the past 4 weeks…

Q1 - How would you describe the pain you usually had from your hip? *Score* None = 4, very mild = 3, Mild = 2, Moderate = 1, Severe = 0
Q2 –Have you had any trouble washing and drying yourself (all over) because of your hip? *Score* No trouble =4, Very little trouble =3, Moderate trouble =2, Extremely difficult =1, Impossible to do =0
Q3 – Have you had any trouble getting in and out of a car or using public transport because of your hip? *Score* No trouble =4, Very little trouble =3, Moderate trouble =2, Extremely difficult =1, Impossible to do =0
Q4 – Have you been able to put on socks, stockings or tights? *Score* Yes easily =4, Little difficulty =3, Moderately difficult =2, Extremely difficult =1, Impossible to do=0
Q5 – Could you do the household shopping on your own? *Score* Yes easily =4, Little difficulty =3, Moderately difficult =2, Extremely difficult =1, Impossible to do=0
Q6 – For how long have you been able to walk (with or without a stick) before pain from your hip becomes severe? Score No Pain = 4, 16-30mins =3, 5 – 15mins = 2, Around the house only =1, Pain severe on walking =0
Q7 - Have you had trouble washing and drying yourself (all over) because of your hip? Score: No trouble =4, Very little trouble =3, Moderate trouble =2, Extremely difficult =1, Impossible to do =0
Q8 – How much has pain from your hip interfered with your usual work (including housework)? Score: Not at all = 4, A little bit = 3, Moderately =2 , Greatly = 1, Total= 0
Q9 - Have you been limping when walking, because of your hip? Score: Rarely/Never =4, Sometimes or just at first=3, Often, not just at first=2, Most of the time =1, All of the time=0
Q10 - have you been troubled by pain from your hip in bed at night? Score: No nights =4, only1/2 nights=3, some nights=2, most nights =1, Every night=0
Q11 - Have you had any sudden, severe pain -'shooting', 'stabbing' or 'spasms' -from the affected hip? Score: No days =4, only1/2 days=3, some days=2, most days =1, Everyday=0
Q12 - After a meal (sat at a table), how painful has it been for you to stand up from a chair because of your hip? Score: Not at all painful =4, Slightly Painful =3, Moderately Painful=2, Very Painful =1, Unbearable=0

Source: Dawson et al. (1996)

3.2.1.1.5 Length of stay (LoS)

The Los data is collected by the HES through calculating the number of days that a patient is in hospital from the date at which they were admitted to the date at which they were discharged. It is therefore possible for each patient included in the study to determine how long (days) they spent in hospital for their THR or TKR. Studies such as Jackson et al. (2013) identified that patients with colorectal cancer stayed in hospital on average longer if they lived further from

the hospital they were attending. The thesis is including the number of days that the patients stayed in the hospital following the THR or TKR as the proxy health outcome measure.

3.2.1.1.6 Missed Appointments (DNA)

Reports such as Hamilton and Gourlay (2002) and SEU (2003) have highlighted the impact of transport problems on patients missing appointments. An estimated 1.5 million hospital appointments per year were missed in the UK due to transport problems (SEU, 2002). Missed appointments were estimated to cost the NHS £ 1bn in 2016/17 with an estimated 8 million missed appointments in total (NHS England, 2018). Critically for the patient, missed appointments can result in issues such as delayed diagnosis and delays to treatment or worse health outcomes due to incomplete follow up following treatment. In the case of THR/ TKR patients have to attend outpatient appointments prior to having the operation and then follow up outpatient appointments so that the surgeon can check that the operation was successful. Missing these may lead to worse health outcomes if issues are not identified. As Lara et al. (2005) found patients living further from the hospital were more likely to miss some follow up appointments.

Missed appointment are not recorded in the HES dataset for inpatient stays, but are recorded for outpatient appointments. The study used the complete requested HES outpatient dataset (Box 1) for those patients with a diagnosis code of OA or RA. This was all patients with a diagnosis code of OA or RA and was not restricted to those who had undergone a THR or TKR. The unattended appointments are recorded in the HES dataset split into a number of reasons why the appointment might not have been attended. These are; appointments cancelled by the hospital, appointments cancelled by the patient, appointments not cancelled by the patient and not attended, and appointments where patients attended late and were seen and whether they attended late and were not seen. The thesis included all outpatient appointments as not attended if the patient had not attended their appointment and had not cancelled. The thesis is interested in whether not attending the appointment is associated with living further away from the hospital. With the idea that missed appointments are a proxy for a patient's health.

3.2.2 Dealing with Missing Health Outcome Data

One of the key observations from the HES-PROMS dataset during cleaning the data was that whilst it was possible to get a complete dataset for the travel times and distances for each of the patients, as this required the home postcode and healthcare facility attended, which is collected through the hospital system, what was missing in a number of cases was the patients'

responses to either all or some of the health measures. The PROMS dataset relies on patients completing the full set of questions both at baseline (prior to undergoing their operation) and at follow up and also that the people entering the data are able to read their answers. Not having complete answers where large numbers of patient data is missing is obviously an issue, as it does not provide the complete picture for the full patient population. A summary of the level of missing data is provided in Table 9. It shows that for the generic self-assessed health measures there were higher levels of missing data for the THR patients compared to the TKR patients. The disease specific questions (OHS and OKS) had much lower levels of missing data at 16.8% and 21.4% respectively than the generic health measures.

Table 9: Summary of missing data by health measure

	Type	Total Sample	Missing baseline and / or follow up
ED-5D-3L Index	THR	4550	33.7%
	TKR	5506	24.9%
EQ-5D VAS	THR	4550	36.6%
	TKR	5506	27.2%
General Health	THR	4,550	34.3%
	TKR	5506	34.0%
OHS	THR	4550	16.8%
OKS	TKR	5506	21.4%
Length of stay	THR/THR		0%
DNA	THR/THR		0%

In terms of having missing data and how critical it is, one of the key aspects to focus on is whether there are any systematic differences between those patients who have missed out some of the questions and those with complete responses. This is tested using the t-test and X^2 tests at the 95% level. A number of methods have been developed for dealing with missing data issues. These methods mostly deal with data that is assumed to be Missing at Random (MAR). Missing at random is interpreted as there "*could be systematic differences between missing and observed values, but these can be explained by the other observed variables*" (Bhaskan and Smeeth, 2014). Whilst there are missing values these can be imputed using evidence from all the other potential explanatory variables (e.g. sex, age, deprivation level, non-missing domains etc.). One of the key methods proposed for imputing data is to use multiple

imputation using a chained approach (MICE) (Royston and White, 2011). This fits with the MARs assumption that the other explanatory variables can be used in the imputation.

The thesis used the MICE methodology implemented in STATA 10.4, with 30 imputations (it is recommended to have as many imputations as the % of missing data). For the EQ-5D-3L data, Simons et al. (2015) found that imputing at the index level was more accurate for smaller sample sizes (e.g. 100), but imputing at the domain level (the EQ-5D-3L index is calculated from 5 questions and the OKS/OHS from 12 questions) was more accurate for larger sample sizes, as is the case for this study. This intuitively makes sense, as with a large number of patients with only one domain missing then the imputation is based on imputing one domain rather than assuming there is no valid information available for the patient. Stata code was written to undertake the multiple imputations at the domain level for the EQ-5D-3L values and then the weights used from Dolan (1997) to convert this data to an index value once the values had been imputed.

A graphical presentation of imputing data using the individual domains is shown in Figure 10 and using index values in Figure 11 for the EQ-5D-3L. It can be observed that when imputing using the domains the imputed data follows the bimodal distribution of the observed data (Figure 10). Whilst 31% of the patients had not completed any of the questions, 69% had completed the self-assessed score for at least one domain in the questionnaire, so imputing by domain allows the model to use all data available. Imputation using the EQ-5D-3L index values (-0.549 to 1) gives a normal (bell shaped) distribution that does not match the observed data, as shown in Figure 11. The imputations for this study show the same findings as Simons et al. (2015). Imputation at the domain level was carried out using an ordered logit model (due to the data being recorded at 3 levels).

The same process was used for the OHS and OKS whereby missing data was imputed at the individual question level (12 questions), so where patients had completed some but not all of the question in the OHS/OKS this data could still be included and not dropped. The rule of thumb is that there should be as many imputations, as percentage of missing data. Thirty imputations were run for each model. In all cases observations were dropped where there was no baseline data (where none of the questions had been answered at baseline).

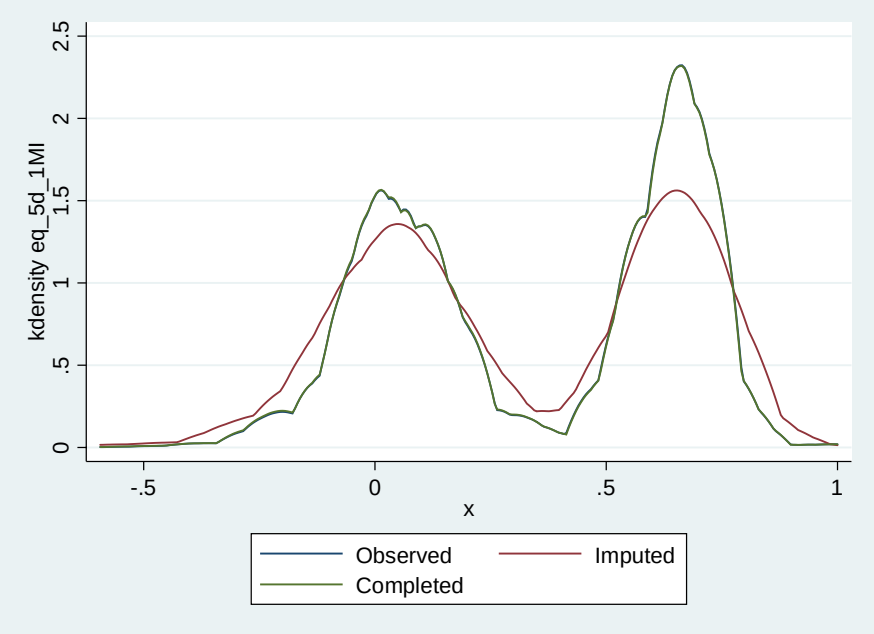


Figure 10: Kernel distribution of the inputted missing EQ-5D-3L data using the individual domains.

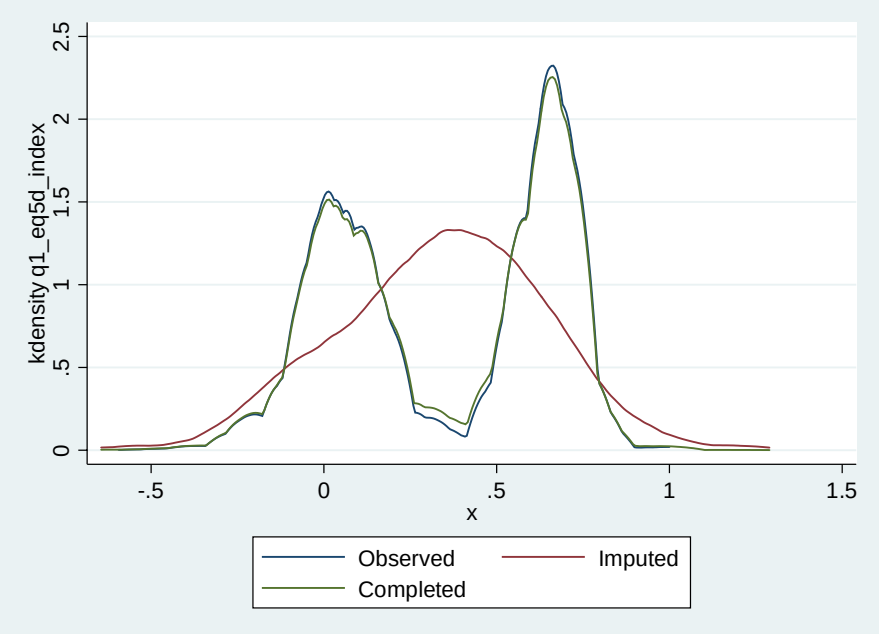


Figure 11: Kernel distribution of imputed missing EQ-5D-3L data using index value (imputed data is represented by the bell curve).

3.2.3 Independent Variable: Travel times and distances to the healthcare facilities

The literature reviewed in Chapter 2 identified a number of methods used to calculate the travel times and travel distances to healthcare facilities. This section describes the methods used to calculate the travel times by bus and car, as a proxy measure for transport accessibility (discussed in section 1.4), as one element of GC in this thesis.

3.2.3.1 Geocoding the origin and destination points

The key data requirements used to calculate the travel times and distances was the origin location (patient's home address/ geographic location) and destination location (healthcare facility address, or nearest healthcare facility). For the HES-PROMS dataset this was of the form:

- Origin – Postcode for the patient's home address (HES code: homeadd)
- Origin – LSOA of the patient's home address
- Destination – Patient's registered GP Practice (HES code: gprach)
- Destination – Nearest GP
- Destination – Hospital where the appointment/ treatment took place (HES code: sitetret or procode).
- Destination – Nearest (researcher defined nearest facility based on all hospitals that undertook THR or TKR or GPs)

The centroid of the patient home postcode was geocoded into easting and northing coordinates. To do this the full set of UK postcodes with corresponding easting and northing coordinates was downloaded from Doogal (2016). The merge of the two sets of data – patient postcode and easting northing coordinates was undertaken using STATA 14 using the *_merge* code and linked by postcode. The same process was completed for the LSOA codes, where the population weighted centroid for each LSOA (and corresponding easting and northing coordinates) accessed through ONS (2018a) was merged with LSOA codes in the HES-PROMS dataset.

The locations of the hospitals attended for the patients' appointments (inpatient and outpatient) were converted from *sitetret* (code of the hospital) or if not available *procode* (provider code of the hospital) to a postcode by interrogating the care quality commission website (Care Quality Commission, 2018). For example, RCB00 corresponds to York hospital, which is located at postcode YO31 8HE. This postcode was converted to easting northing coordinates, using the same method described above. The GP practice codes from the HES dataset (registered GP)

were converted to a practice geographical location using the GP location file (EPRACCUR file) accessed through the NHS Digital website (NHS Digital, 2016b). This file includes the name and address details of all the GPs in England alongside their GP practice codes. These centroids of these postcodes were also geocoded into easting northing coordinates by merging the file with the downloaded easting and northing coordinates in STATA 14. In total patients attended 31 different hospitals for their THR/TKR both within and outside WY. The patients were registered at 358 different GP practices both within and outside of the WY region.

3.2.3.2 Calculating the travel times and distances

As discussed in Chapter 1, whilst transport accessibility is a multi-dimensional construct with different implications for different individuals the most common method that is used in the literature as shown by the review in Chapter 2 is to use a proxy measure of travel time or distance to healthcare facilities. Drawing from the literature the three key methods that have been employed to calculate travel times and distances using GIS are:

- Straight-line distance (Euclidean distance)
- Car driving distance (using the road network)
- Car travel time (using the road network)

In addition to these the travel times by public transport were also calculated to provide a comparison. The methods used to calculate each of these approaches are now described.

3.2.3.2.1 Straight-line distance

The straight-line distance (or Euclidean distance) is the distance using a straight-line from the origin location to the destination point. The study used the *Near tool* in ESRI ARCMAP 10.2.2 to calculate the straight-line distance from the geocoded home postcode and LSOA to the actual and nearest facilities. This is the most straightforward measure of distance to calculate as it requires the starting and end points and draws a straight-line between the two. The main criticism of this approach is that very few journeys are made in a straight-line, as for example rivers and one way systems get in the way. This will mean that the results using this measure will tend to underestimate the travel distance. This method was used by over 25% of the studies included in Chapter 2.

3.2.3.2.2 Road distance and road travel times

The next approaches are to calculate the travel distances and travel times using the road network. This is an improvement on the straight-line distance as it takes account of the fact that very few journeys are made in a straight-line and does this by using the road network. The study

used the Ordinance Survey (OS) Integrated Transport Network Layer (ITN) as the road network. This was accessed in September 2016 through (EDINA Digimap Ordnance Survey Service, 2016). The OS ITN includes the road network and road routing information for the whole of Great Britain. This includes ~ 544,000km of roads, which are classified by name and road type. The network includes information that might affect how a driver might travel along a route including; one way streets, pedestrian zones and access restrictions, which will restrict the route and ultimately road network travel times. One of the main decisions to be made when applying the ITN is to determine the travel speeds to be used along the routes. The default is to use the speed limits on the roads. Findings published by the Department for Transport (DfT) showed that in 2015 84% of cars exceed the 20mph speed limit, 52% exceed the 30mph limit, 9% the 60mph speed limit for single carriageways and 46% the speed limit of 70mph on a motorway in free flow conditions (DfT, 2016). On the basis of this information together with the lack of knowledge about the times of day when the patients were travelling for their appointments and the mix between urban and rural areas the national speed limits by road type were applied to the model. With the assumption that at some points in the day the journey will potentially be faster than using the speed limits and at other times slower, as it doesn't account for congestion levels. Studies such as Haynes et al. (2006) have explored whether travel times to hospital using GIS are comparable to the travel times reported by patients for the same journey by car. They found that 77% were within 10 minutes of the patient reported journey times and 90% within 15 minutes of the road network estimated travel times and concluded that the GIS estimates "*were more appropriate for modelling purposes because they represented average conditions"* ((Haynes et al., 2006)(p7).

The study used the Network Analyst tool in ESRI ARCMAP 10.2.2 to calculate the travel times and distances using the origin and destination locations and the ITN network. The process was automated by programming in Python, which is an object oriented programming language that allowed the process to be automated and as a result speed up the process of calculating all the travel times and distances, as they can run in a loop. The process was intensive and time consuming, as it needed to be run for each GP practice in the dataset and hospital provider individually. Due to the ethical approval process described in section 3.1.1.1 the data had to be accessed through a password protected computer on the University of Leeds campus and could only be accessed in the office (not remotely), which lengthened the time needed to run the programme and determine the travel times and distances.

3.2.3.2.3 Travel times by public transport

A number of studies in the review in Chapter 2 had considered travel by bus to hospital for patients. For example, Jones et al (2010) calculated whether patients had access to a weekday bus service within 800m of their home and Moist et al (2008) asked patients how long it took them to get to the dialysis unit and how they got there. However none of the studies reviewed had calculated the bus travel times using patient data. The transport software Visograhy TRACC produced by Basemap Ltd was used to calculate the travel times by public transport from the patients home postcode and LSOA to the hospital (nearest and actual attended). The study did not calculate the travel times to the GP by bus, as it was not possible to automate the bus travel times, so was not possible in the timeframe.

The bus travel times were calculated using the Visography TRACC software, the National bus scheduling data and public transport bus stop data. The public transport stop data for England was accessed through the National Public Transport Access Nodes (NAPTAN, 2016). This provides the coordinates of all public transport stops (including bus stops) in England. The public transport scheduling data was accessed through the Traveline National Dataset ((TNDS, 2016). This includes the detailed information on all bus routes in England. Those bus routes relevant for this study were cut from the National data. Visography Tracc uses the ITN, bus schedules and bus stops to calculate the travel times by bus from a given origin to destination point. The origins (home postcode and LSOA) and destinations (nearest and attended) need to be uploaded individually.

One of the key differences with the bus routing data is that generally the bus does not go directly from outside of an individual's home and in many cases requires an interconnected bus journey involving multiple buses. In order to capture these differences a number of additional assumptions are included in the algorithm for calculating the travel times. Using the same approach as used by DfT (2017) to calculate the travel time by bus and walk to local facilities the study assumed that patients could walk a maximum of 800m to the bus stop at a walk speed of 4.8Km/h at the start of their journey. For example, an individual who walked 500m to the bus stop and then walked 500m from getting off the bus to get to the hospital would add 12.5 minutes to their journey time. It also means that patients who would have had to walk beyond 800m to get to the first bus stop would be recorded as not having an accessible route. This seems a reasonable assumption to make as the patients are likely to have mobility issues limiting their ability to walk long distances. Where patients have to change buses (e.g. one bus does not go all the way) an assumption was included that there should be a maximum 500m interconnection distance. This would result in an inaccessible route if the patient had to catch

two buses to get to the hospital and the distance between getting off the first and getting onto the second was greater than 500m to walk. This walking distance between buses is included in the travel time calculations, as is a 5 minute interchange penalty (the time allowed to get off one bus and onto the next). The software uses the routing information to calculate the fastest route to get from the starting to end location including all the sections where patients would have had to walk. One of the disadvantages of using bus scheduled data and home to hospital travel times by car (rather than the actual journey data) is that it is based on a perfectly running network, so not accounting for changes to the schedule due to road closures, the weather, slow running schedules, congestion etc… Data that can account for differences in road speeds is currently being collected by Basemap and would be available in the future, but without knowledge about what time the patients have travelled to the hospital for their appointment additional assumptions would be needed to apply this information to the data.

3.2.3.3 Comparing between the travel times and distances

A number of studies in Chapter 2 had used differing combinations of home location and destination descriptors (e.g. nearest hospital, actual hospital attended). T-tests were run to assess whether there were any statistically significant differences between the distance and travel time combinations, as set out in Table 10. The t –test was used, as it allows an assessment of whether there is a statistically significant difference between the means in combinations of pairs. For example, is there a statistically significant difference in the means between calculating the road network distance using the home postcode and hospital attended vs. the proxy for the home address (LSOA) and hospital attended. The 95% confidence interval (CI) around the mean is shown to assess whether there is a 95% confidence that the means are different to each other.

Table 10: Methods for calculating the travel times and distances to the Hospital

Origin	Destination	Straight-line Distance	Road Network Distance	Road Network Travel Time	Bus Network Travel Time
Home Postcode/ Address	Hospital	x	x	X	x
Home Postcode/ Address	Nearest hospital	x	x	X	x
Proxy for home address	Hospital	x	x	X	x
Proxy for home address	Nearest hospital	x	x	X	x

3.2.3.4 Additional Transport Data

The HES-PROMS dataset did not contain specific data on how far away patients lived from the hospitals they were attending or their registered GP practice, so this data needed to be calculated as part of this thesis, as discussed above. The PROMS dataset did have questions within the OKS and OHS on how easy patients find it to walk and how easy is it to get into a vehicle. The following questions (and potential answers) are reproduced below in the context of THR patients:

- *During the past 4 weeks, for how long have you been able to walk before pain from your hip becomes severe? (with or without a stick) – Answer not at all, around the house only, 5 – 15 mins, 16 – 30 mins, no pain / more than 30 mins.*
- *During the past 4 weeks have you had any trouble getting in or out of your car or using public transport because of your hip? – Answer impossible to do, extremely difficult,* moderate trouble, very little trouble, No trouble at all.

These two questions have been analysed using descriptive statistics in this thesis. Someone who finds it extremely difficult to get in/ out of a car may have issues with transport accessibility in terms of the discomfort it creates or not being able to use public transport.

3.2.4 Other explanatory / predictor variables

As discussed in Chapter 1 there are a large number of potential determinants of a patient's health, which range from differences in age and ethnicity to whether patients live alone or have comorbidities. It is important to ensure (as far as is possible) that what the study is measuring is the association between travel time or distance and the health outcome and not some other association. The review of potentially predictive factors identified in section 3.2.2 and the introduction on health inequalities in Chapter 1 included: *age, gender, BMI, education/ SES, ethnicity comorbidities, alcohol consumption, vitamin D deficiency, smoking, deprivation, living alone, pre-operation radiology severity, pre-operation function and pain, pre-operation HRQoL, mental health and post operation health outcomes, time on the waiting list and length of stay in hospital, type of hospital.* The HES-PROMS dataset includes a subset of these potential explanatory variables that could be associated with the outcome measure (health outcome) or in some cases could be argued to be associated with both the travel time measure and the health outcome measure as a potential confounder.

Gender was identified as being a potential determinant of difference in health outcomes following THR and TKR replacements (Jüni et al., 2010). Older patients have been shown to have

lower gains in health outcomes following a TKR than younger patients (Williams et al., 2013) and there have been shown to be differences in access to THR and TKR and health outcomes for differing ethnic groups (Smith et al., 2017) and by deprivation levels (Edwards et al., 2018) living arrangements (Edwards et al., 2018) and by number of comorbidities (Podmore et al., 2018)

A summary of the key variables available as potential explanatory variables from the HES-PROMS dataset is provided in Table 11. These include variables that were directly available from the data (e.g. gender, ethnic group, and days in hospital) and variables that needed to be coded using the data (e.g. Charlson Index that focuses on comorbidities and type of hospital). As can be seen it includes a subset of variables that have been considered in the literature.

Whether a patient had comorbidities was one variable, which could affect a patient's health outcome. The study used the Charlson Comorbidity Index calculated using Charlson et al. (1987) and coded in STATA 14. This method determines a score for comorbidities based on the ICD 10 diagnosis codes (WHO, 2016) that have been entered against each inpatient appointment within the HES dataset. For example, a patient may have no comorbidities, whilst another will have multiple (including for example cancer or heart failure) and as a result have a higher Charlson Index score. The study decided to convert this score (between 0 and 12) into a categorical variable as shown in Table 11, as there were fewer patients as the number of comorbidities increased.

The study also wanted to include in the analysis a proxy for the quality of the hospital, as this may impact on the health outcomes of the patients who were treated there. The hospital quality indicator was derived from Care Quality Commission (2018) assessment for each hospital as a whole (e.g. "needs improvement" "good" or "excellent"). In addition to the measure of hospital quality the study included whether the patient was treated at an NHS hospital or an independent private sector provider. This was important as patients treated in the private sector have differing characteristics to those treated by the NHS, where the NHS treats the more high risk cases. Chard et al. (2011) reported that patients treated for a TKR or THR in the private hospitals were fitter for surgery, had fewer comorbidities and higher EQ-5D-3L index scores and OHS/OKS score before having the operation.

To determine which of the available variables to include, the correlations between potential explanatory variables (strength of association) were examined. Including two highly correlated variables, as independent variables in the regression analysis will cause problems with collinearity. This has a disabling effect on the coefficient estimates for the independent variable, as it causes an increase in the standard errors of the coefficients, which can make some variables

incorrectly statistically non-significant. Pearson's correlation coefficient and Phi Coefficient were employed to assess the strength of association between the variables (test for collinearity) (Hinkle et al., 2003). Pearson's correlation evaluates the linear relationship between two continuous variables, for example, days in hospital and travel time to hospital. Phi coefficient evaluates the correlation between two categorical variables (e.g. gender and Age groups). The coefficient ranges between – 1 (negative relationships) and + 1 (positive relationships). A summary of how to interpret the coefficients strength of association is provided in Table 13.

Table 11: Potential explanatory variables available / calculated from the database

Dataset	Variable	Description
HES	Sex	Coded 0 = male, 1= female
	Age	Coded: 1 = < 60 2= 60 – 80 3= >80
	Ethnicity	Coded: 0 = white British , 1 = other
	Comorbidities (Charlson Index)	Coded: 0 = none, 1 = 1/2, 2 = 3 - 12
	Days on the waiting list	Continuous
	Days in Hospital	Continuous
	Index of Multiple Deprivation	quintiles
	Attended Nearest Hospital	Coded: 0 = nearest, 1= not nearest
	Hospital Type	Coded: 0= NHS, 1 private provider
	Travel time / Distance to the hospital/ GP	A range of methods
	Season	Coded: 0 = not winter 1 = winter
PROMS	Living alone	Coded: 0 = cohabiting , 1=alone
CCQ*	Quality of the Hospital	Coded 0 = Needs improvement 1 = Good/ Outstanding

Table 12: Correlations between covariates (using Pearson's Correlation Coefficient and Phi Coefficient)

	Baseline SAH	Follow up SAH	Sex	Ethnicity	Age	Deprivation (IMD)	Living Alone
Baseline SAH	1						
Follow up SAH	0.3203*	1					
Sex	-0.1335*	-0.0435*	1				
Ethnicity	-0.0158	-0.0269*	0.0131	1			
Age	0.0634*	0.0661*	0.0849*	-0.0285*	1		
Deprivation	-0.1496*	-0.1590*	0.0240*	0.0930*	-0.1025*	1	
Living Alone	-0.0343*	-0.0238*	0.2095*	-0.0256*	0.2399*	0.0556*	1
Comorbidities	-0.0989*	-0.1321*	-0.0131	-0.0147	0.1256*	0.0782*	0.0440*
Days on the waiting list	-	-0.0677*	-0.0088	-0.0050	-0.0574*	-0.0094	-0.0094
Days in Hospital	-	-0.1685*	0.0406*	-0.0384*	0.2232*	0.0269*	0.1529*
Type of Hospital	0.0937*	0.0801*	-0.0013	0.0774*	-0.0005	-0.0815*	-0.0097
Hospital Quality	0.0474*	0.0835*	0.0276*	0.0276*	0.0164	-0.0967*	0.0062
Rural/ Urban Location	0.0447*	0.0513*	-0.0105	-0.0154	0.0083	-0.1573*	-0.0224*
Travel time to hospital	0.0379*	0.0438*	-0.0202*	-0.0783*	-0.0432*	-0.2195*	-0.0373*

	Comorbidities	Days on the waiting list	Days in Hospital	Type of Hospital	Hospital Quality	Rural Urban Location	Travel time to hospital
Comorbidities	1						
Days on the waiting list	0.0429*	1					
Days in Hospital	0.1380*	0.0113	1				
Type of Hospital	-0.0564*	-0.1277*	-0.1400*	1			
Hospital Quality	-0.0370*	-0.2722*	-0.1246*	0.4173*	1		
Rural/ Urban Location	-0.0355*	0.0130	-0.0197*	0.0246*	-0.0097	1	
Travel time to hospital	-0.0681*	-0.0349*	0.0057	-0.068*	0.1482*	-0.036*	1

(Legend * $p<0.05$)

Table 13: Interpretation of correlation coefficients

Positive Correlation	Negative correlation	Correlation
0.9 to – 1.00	-0.9 to – 1.00	Very High
0.70 to 0.90	- 0.70 to - 0.90	High
0.50 to 0.70	- 0.50 to - 0.70	Moderate
0.30 to 0.50	-0.30 to - 0.50	Low
0.00 to 0.30	0.00 to – 0.30	Negligible

Adapted from (Hinkle et al., 2003)

The results presented in Table 12 show that travel time to hospital was negatively correlated with gender, ethnicity, age, deprivation, living alone, comorbidities, days on the waiting list, types of hospital and rural/urban location. As can be seen from the table that whilst zero correlation was not recorded for any pair of variables the highest correlations were with deprivation (as deprivation increases patient travel time to hospital declines) and hospital quality (as hospital quality improves travel time to hospital increases). On the basis of Table 13 all of these correlations fit into the 'negligible' correlation category, so would not be considered an issue to include in the model.

The study used the entry approach (including all explanatory variables at once) or a priori knowledge to determine variables to include in the regression models. All included variables had been identified in the literature as potential predictors of differences in health outcomes for this group in the population and had been assessed for collinearity. All variables that were included either had evidence of being associated with the dependent variable (health outcome) or were being tested by this research (e.g. travel times). The other main approach that could have been used to determine which variables to include in the models is the stepwise approach whereby variables are included or removed from the model based on whether they improve or reduce the predictive ability of the model using a computer algorithm. There has been a lot of criticisms of stepwise approaches in the literature including that it has the potential to over fit the model and include variables that have no associations to the outcome measure (Derksen and Keselman, 1992; Babyak, 2004). Therefore it was decided on the basis of this to use the entry approach.

3.2.4.1 Statistical Models

The next stage was to determine which statistical models would best fit the data. The different health measures and final statistical models used to model the data are summarized in Table 14. A description of these methods and why they were selected is provided next.

Table 14: Health Measures (Models used)

Dataset	Measure	Health Measure	Range/ scale	Model
PROMS	EQ-5D_3L	Generic	-0.594 – 1.0	OLS
	EQ5D - VAS	Generic	0 - 100	OLS
	General Health	Generic	Excellent, Very Good, Good, Fair, Poor	Ordered Logit Model
	OHS	THR	0 – 48	OLS
	OKS	TKR	0 – 48	OLS
HES	Length of Stay	Generic	Days	OLS
	DNA	Generic	Attended/ DNA	Binary Logit Model

Starting with the EQ-5D-3L a number of models were considered to evaluate the values, which range between -0.549 and 1. This index has been the subject of much discussion about which regression methods are most suited to use. Most recently the adjusted limited dependent variable model (ALDVMM), specifically designed to analyse this data was proposed. This method caps the index values between - 0.549 and 1 (similar to a Tobit model (Tobin, 1958)) and adjusts to account for the gap in index values between 0.883 and 1 and then employs a mixture model, so identifying different groups within the data (Hernandez -Alva et al., 2012; Hernandez -Alva and Wailoo, 2016). As the study was interested in changes in scores (whether patients health improved as a results of the THR/TKR) the ALDVMM method was not suitable as it was designed to take account of the distribution of the EQ-5D-3L index and not the distribution of the change scores. The method that was chosen to analyse the data was the ordinary least squares (OLS) because of a match of assumptions with OLS, as discussed below.

In the simplest form the study focused on whether the change in EQ-5D-3L health measure was associated with the baseline EQ-5D-3L health measure and travel time OR distance controlling for baseline health. It was important to control for the baseline EQ-5D-3L index, as individuals had differing starting points. A patient with a higher pre-op index value would have less potential scope for improvement than those with a lower pre op index value. By controlling for the baseline health score this controls for this issue (regression to the mean). For example, an individual who started at an index value of 0.67 would be able to achieve a much smaller gain (even if the follow up score was 1) than an individual whose starting point was -0.549. This first model is shown in Equation 2.

$$Y^*_i = \alpha + \beta_1 X1_i + \beta_2 X2_i + \varepsilon_i \qquad \textit{Equation 2}$$

$$\varepsilon_i \sim N(0, \sigma^2)$$

Where: $_i$ = *refers to observation number, Y = health measure (change in score),* α *= constant term (y intercept),* X_1 *= health measure Baseline (pre operation),* X_2 *= transport accessibility measure to hospital (travel time or distance),* ε*= random error term*

Equation 3 expands this to control for other explanatory variables. The multivariable model included all the independent variables (travel time plus the other explanatory variables), as described by Equation 3.

$$Y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_M X_M + \varepsilon \qquad \textit{Equation 3}$$

$$\varepsilon_i \sim N(0, \sigma^2)$$

Where: *Y = Change in the health measure (post operation – pre operation),* α *= constant term,* X_1 *= health measure (pre operation),* X_2 *= transport accessibility measure to hospital (travel time or distance),* $\ldots + B_M X_M$ *= All other included explanatory variables.* ε*= random error term*

In order to apply an OLS model to the data the study is making the parametric assumption that the data comes from a population with a normal distribution. This assumes that the values from the population (from which the sample was taken) are normally distributed. The central limit theorem states that "given random and independent samples of N observations each, the distribution of sample means approaches normality as the size of N increases, regardless of the shape of the population distribution" (Anderson (2010),p 1). It is widely reported that 30 is the minimum sample size required to satisfy this 'large' N (Anderson, 2010). In addition to the study having a large sample size and a linear relationship between the dependent and explanatory variables, the following tests were run for each model to see whether it was suitable to apply an OLS to the data. These were:

- Are the residuals (error terms) normally distributed? This was tested by plotting the residuals as a histogram and including a normal curve for comparison.
- Are the residuals homoscedastic? This was tested by plotting the residuals against the predicted values. For the residuals to be homoscedastic there should be no pattern to the data. Where the residuals were found to be heteroscedastic (patterns identified) this was controlled for using robust errors in the models.
- Is there any multicollinearity? Are the predictor variables highly correlated with each other? This was tested by calculating the variance inflation factor (VIF).

The tests were applied to all the models and on the basis of this the OLS was chosen as the best approach to be used for the EQ-5D VAS, OHS and OKS. An example of the tests for the OKS model are shown in Figure 12 to assess whether the residuals were normally distributed. In Figure 13 to allow an assessment of whether the residuals are homoscedastic (whether there is a pattern to the data). The assessment found that the data was heteroscedastic (there was some pattern to the data) and so robust errors were included in the OLS statistical models. Table 15 presents the results of the Variance Inflation Factor (VIF) to test to see the levels of multi collinearity between the variables in the model. Predictors that are highly collinear (linearly related) can cause problems in estimating the regression coefficients. . A value of VIF of 1 indicates no correlation. For the models the average VIF was 1.39 indicating that there was low correlation between the variables. Hair et al. (2014) argue that as a rule of thumb *"values of VIF >10 indicate large amounts of multicollinearity"* (p206), so in the case of the models in this thesis we can say there were not large amounts of multicollinearity.

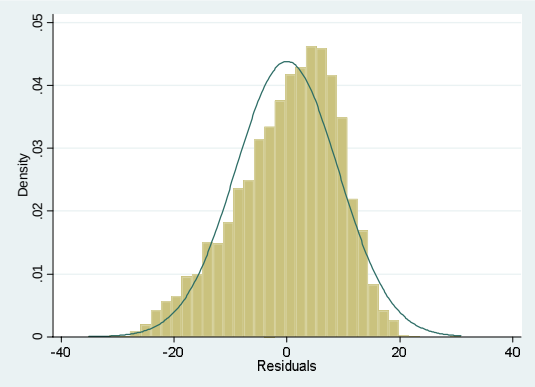


Figure 12 Kdensity plot of the residuals (OKS model categorical travel times to hospital)

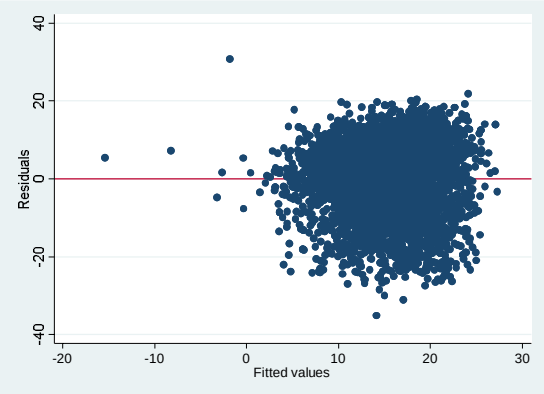


Figure 13: Scatter plot of residuals vs fitted values (OKS model categorical travel times to hospital)

The OLS approach was also used for the LoS in hospital model, which was also a continuous variable, but required modifications to Equation 1 and 2, as baseline results were irrelevant. The OLS approach was also used to assess whether travel time or distance to the GP was associated with pre operation health scores. Again in this case there was no baseline data to control for in the model.

In developing the model the study did consider whether to include interactions in the model particularly between the categories of deprivation and travel times, as this had been considered in some of the studies in the systematic review (e.g. Crawford et al. (2009). The interaction effects would in this case represent the combined association of deprivation and travel time on the health outcomes/ change in health outcome. The study did not find sufficient evidence of

an interaction effect (a statistically significant interaction effect ($p<0.05$)), so dropped them from the models presented in the thesis.

Table 15: Testing for Multi collinearity (OKS model categorical travel times to hospital)

	Variable	VIF
Baseline Health	Baseline OKS score	1.17
Travel time (Baseline 0 – 10)	10 – 20	1.39
	20 – 30	1.51
	> 30	1.05
Gender	Female	1.11
Age groups (baseline < 60)	60 – 80	1.57
	> 80	1.65
Deprivation Quintiles (baseline = least deprived)	2	1.74
	3	1.83
	4	1.96
	5	2.06
Length of stay in hospital	Days	1.15
Comorbidities (baseline = o)	1 -2	1.06
	>2	1.08
Living Arrangements (baseline = cohabiting	Alone	1.11
Ethnic Group (Base line = White British	Other	1.03
Hospital Provider(baseline = NHS)	Private	1.31
Hospital Quality (baseline = Needs Improving	Good /Excellent	1.31
Average VIF		1.39

Measures of fit can be used to assess how well the models fit the data. In terms of evaluating the fit of the results of the OLS, the study has used the R^2 and RMSE. The R^2, is a measure of how close the real data points are to the fitted regression line. An R^2 of 1 indicates that the OLS model explains all the variability. It is often used in the health economics literature due to its intuitive interpretation on a scale between 0 and 1. For example an $R^2 = 0.18$ can be interpreted as 18% of the variation in the dependent health variable can be explained by the independent variables in the model. The Root Mean Square Error (RMSE), which is the square root of the variance of the residuals. It can be interpreted as the standard deviation of the unexplained variance and is a good measure of how accurately the model predicts the outcome. Lower values of RMSE indicate a better fit. Other approaches that are commonly used to assess the fit of OLS regression models include the adjusted $R^{2,}$, which adjusts the $R^2$for the number of predictors in the model. Adding more predictors to the model can inflate the R^2 value. The adjusted R^2 for the models were reviewed, but are not included in the results tables.

The study included travel times as both a continuous variable and as a categorical variable in the models. The models with the better fit in the case of the OLS models with higher R^2 and lower RMSE tended to be the ones with travel time included as a categorical variable, which are presented. Other approaches would have been to include travel times as a polynomial (e.g. quadratic and cubic), but there was no indication that the association between the independent variable and dependent variable were nonlinear, so these were not employed.

In terms of the coefficients the study is assessing whether the p-values are <0.1, < 0.05 and < 0.001. This means that the null hypothesis ($H_0 : \beta 1 = 0$) can be rejected ($H_1 : \beta 1 \neq 0$) if the p values are less than the thresholds. For example, if the p value for the coefficient for an independent variable was 0.04 then the null hypothesis could be rejected at the 10% and 5% significance level, but not at the 0.1% significance level. Having a result that is statistically significant at the 5% versus 10% level the less likely the model will conclude an association between the dependent variable and the independent variable, when there is no association. The literature has focused predominantly on statistically significance levels of below 0.05 (p<0.05), which indicates a 5% risk of making this type of error widely attributed to Fisher (1950). A number of authors have commented that the p<0.05 is somewhat an arbitrary threshold, that serves a general purpose (Stigler, 2008). One of the criticism of this threshold is that using just p<0.05 means that those results with a p value p<0.049 are deemed statistically significant whilst those at p<0.051 are not. It is common practice in the field of health economics to present a range of p values (e.g. p<0.1, 0.05 and 0.01) to show the range at which different variables are statistically significant.

OLS models are not suitable for data that is binary (e.g. missed / attended the appointment), as it would violate the assumption that there is a linear association, a better fit are binary logistic regression models. In logistic regression the outcome Y (independent variable), which is a binary 0 or 1 outcome is transformed using a logit transformation (see equation 4) so the dependent variable becomes $\ln\left[\frac{p}{1-p}\right]$ rather than Y, as used in the OLS equation shown in Equation 2.

$$ln\left[\frac{p}{1-p}\right] = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n + \varepsilon \qquad \textit{Equation 4}$$

Where:

- *ln = the natural log of the odds that Y equals one of the binary categories (0 /1)*
- $\left[\frac{p}{1-p}\right]$ *= the odds ratio (whereby p = the probability of an event occurring e.g. person having access to a car when needed or probability Y = 1))*
- β_0*= the constant*

- $\beta_1 \rightarrow \beta_n$ = *the independent variable coefficients for the n independent variable* x_1 to x_n

The results are interpreted in a similar way to the OLS model. It is not possible to use the R^2 to measure model fit, but a pseudo R^2 can be determined, which allows comparisons between the model with and without covariates (unadjusted and adjusted). The interpretation of the p values are the same. P value ≤ 0.1, 0.05, 0.001 allows you to reject the null hypothesis that the independent variable coefficient equals zero (H_1 : β1 ≠0) at the 10%, 5% and 0.1% levels and conclude that there is a statistically significant association between the independent variable and the dependent variable at that level.

Binary logit regression models are a good fit for data with binary outcomes, but the self-reported general health is ordinal data that has more than two categories (Excellent, Very Good, Good, Fair, Poor). The method commonly used to model these type of data is the ordered logistic regression model. It caters for ordinal dependent variables (such as the 5 point Likert scales used to measure ease of access and self-reported general health), where the data is ordered. The formula is shown in Equation 5, where the unobserved (latent) variable y* is a function of the constant and independent variables, as for the OLS, but that the error term is assumed to have a logistic distribution.

$$y_i^* = \beta_0 + \beta_1 X_1 + \beta_2 \beta_2 + \cdots + \beta_n X_n + \varepsilon_i, \qquad \varepsilon \sim logistic(0, \frac{\pi^3}{3}) \qquad \textit{Equation 5}$$

The continuous unobserved (latent) variable y* is divided into observed, ordinal categories (in this study 4 categories) using the thresholds of τ_0 to τj.

$y_i = j \quad if\ \tau_{j-1} \ll y_i^* < \tau_j \ \ for$ j = 1 to 4

Where τ_0 = - ∞ and τj = ∞ . For the self-reported general health the observed categories determined by the model are:

$$y_i \begin{cases} 1 = Excellent\ , Very\ Good & if\ \tau_0 = -\infty \leq y_i^* < \tau_1 \\ 2 = Good & if\ \tau_1 \leq y_i^* < \tau_2 \\ 3 = Fair & if\ \tau_2 \leq y_i^* < \tau_3 \\ 4 = Poor & if\ \tau_3 \leq y_i^* < \tau_4 = \infty \end{cases}$$

One of the main assumptions of the ordered logit regression model is that there is no difference in the coefficients produced when comparing between the different outcome categories i.e. the proportional odds are the same of going from very easy to quite easy and quite difficult to very

difficult for example. The Brant Test (Brant, 1990) assesses whether this assumption holds – whether any deviations from the model (differences when comparing between categories) are bigger than would be expected by chance. If the assumptions do not hold then the option available that is a better fit for the data would be to use a generalized ordered logit model, which updates the model to allow for different coefficients (betas) between differing categories (Williams (2006)). As for the binary logistic regression a pseudo R^2 can be calculated to assess the fit of the models and used to compare between models, but it cannot be used (unlike the R2 for OLS) to say how much of the variance is explained by the model.

For each of the methods the statistical model was run firstly unadjusted (the dependent health / wellbeing variable and independent transport variable plus) and then adjusted for the identified other potential explanatory variables.

3.2.4.2 Interpreting the results from the models

The study uses the health outcomes in the HES PROMS data in two ways. Firstly to see whether transport accessibility (as measured using travel time from the patient's postcode to the hospital/ GP) is associated with differences in self-reported health (at baseline), LoS (number of days) and outpatient appointments either attended or not attended. Secondly, to explore whether transport accessibility is associated with differences in the change in health outcome (6 months post operation minus pre –operation) The justification for using the change in score is on the basis that *"the main purpose of medical treatment is to enhance the patients' health" (Blome and Augustin (2015) p110).* The measurement that we have of this enhancement in the case of THR and TKR is how much HRQoL improves (or changes) from before the operation to after from the perspective of the patient. This is the main justification for collecting the PROMS data from patients both before their operation and 6 months after, in order to enable an answer to the question - Has the operation enhance the patients' health?

The results are being tested in both cases by seeing whether the differences in the results are statistically significant ($p<0.05$). For the calculations including change in score the results are also being assessed using the minimal clinically important difference (MCID) (e.g. would patients notice any difference in their health – so does the change really matter). The implication is that the study might be able to detect a statistically detectable change, but it might be clinically meaningless to the patient. For this second method a body of literature has been developed using the PROMS questions to define a MCID. MCID is defined as *"the smallest difference in score in the domain of interest which patients perceive as beneficial and which would mandate in the absence of troublesome side effects and excessive cost a change in the patient's management"* (Jaeschke et al., 1989) (p408).

To operationalise this definition two key methods have been used in the literature to calculate what this MCID should be. These are the anchor based and distribution based methods. The anchor based methods investigate how the change in score in the health measure compares with change in the "anchor" reference question, which seeks to determine whether the patient is better following the operation. For example, Beard et al. (2015) calculated the MCID for the OHS and OKS following a THR and TKR and used the global transition item anchor question:

"Overall, how are you <hip/knee> problems now, compared to before your operation? With five response categories: much better…a little better…about the same…a little worse…and much worse" (p74)

Following this either a statistical test (e.g. average change) or a receiver operating characteristic (ROC) curve is used to identify the MCID, as the threshold best separating the anchor question thresholds. For example, what is the average change in score between "about the same" and "a little better". One criticism of this method is that it is not suitable for conditions where the majority of patients do improve, so there is less ability to discriminate, which as noted earlier is the case for THR and to a lesser extent TKR. The alternative method is the distribution based methods which rely on calculating variations on the standard deviation of the data, the standard error of measurement and the effect size. Using this method has similar issues to the statistically significant calculations, as they may not be relevant to what is clinically important (Maltenfort and Diaz-Ledezma, 2017). Research has shown that the MCID differs across diseases and health outcomes, so requires different values. It is also important to note that there are variations in the timeline where these calculations are made – some include follow up of 6 months, others 1 year, which are likely to lead to some differences.

NICE (2014b) state that the following MCIDs should be used in assessments for THR and TKR (in clinical trials) on the conclusive or non-conclusiveness of effects; for OHS/ OKS this in the range of 5 to 7. Beard et al. (2015) reported that using the anchor method and ROC analysis resulted in minimal important changes of 5 points for the OHS and 4 for the OKS following hip and knee joint surgery respectively. Whereas Murray et al. (2007) suggests the thresholds could be lower than 3. There is therefore some dispute in the literature as to what the MCID for OHS and OKS should be. For the EQ-5D-3L NICE (2014b) suggest basing the MCID threshold at an average of 0.074 and range - 0.011 – 0.140. This is based on research undertaken by Walters and Brazier (2005).

3.3 Results

The results are presented in this chapter by first describing the characteristics of the participants. This is followed by the results from the data on travel times and distances to the healthcare facilities and then an exploration of the health outcomes for this group of patients and presentation of the results of the statistical models

3.3.1 Who are the THR and TKR patients?

In total there were 4,550 THR patients and 5,506 TKR patients included in the sample that also had an OA diagnosis summarized in Table 16. In summary for those who had a THR 40.7% of the population were male, 88.93% were White British, 29% of them lived on their own, 34.78 had comorbidities, 83.43% were treated in an NHS hospital, 43% of them attended a hospital that had a good or excellent CQC rating. They travelled on average 14.80 mins to the hospital that they attended. In summary for those who had a TKR 46.2% of the population were male, 85.5% were White British, 25.5% lived on their own, 40,62% of them had comorbidities , 85.85% were treated in an NHS hospital, 39% of them had attended a hospital with a CQC rating of excellent or good. They travelled on average 14.5mins to the hospital that they attended. They attended 31 different hospitals, as shown in Map 2.

A comparison between the two subgroups (THR and TKR) is provided in Table 16 to assess whether there are any differences in patients using t- test and X^2. It can be seen that the patient groups differ in a number of ways. There are proportionally more males in the TKR subgroup. Patients in the TKR group are on average older than those in the THR group. TKR patients live on average in a more deprived area, measured using the index of multiple deprivation (IMD score). There is a higher percentage of White British patients in the THR group. THR patients are more likely than TKR patients to be living alone. TKR patients on average spend longer on the waiting list than THR patients and spend longer in hospital following the operation. Whilst THR patients were statistically significantly more likely to have attended a hospital that was classed as excellent/ very good. There were no statistically significant differences between THR and TKR patients in terms of the distances and travel times to hospital at the 95% CI level, but there was a significance difference at the 90% level for travel times to hospital using the t-test ($p=0.08$). There was no statistically significant differences in terms of the type of hospital attended (NHS vs. privately provided), or where the patient lived (urban vs. rural).

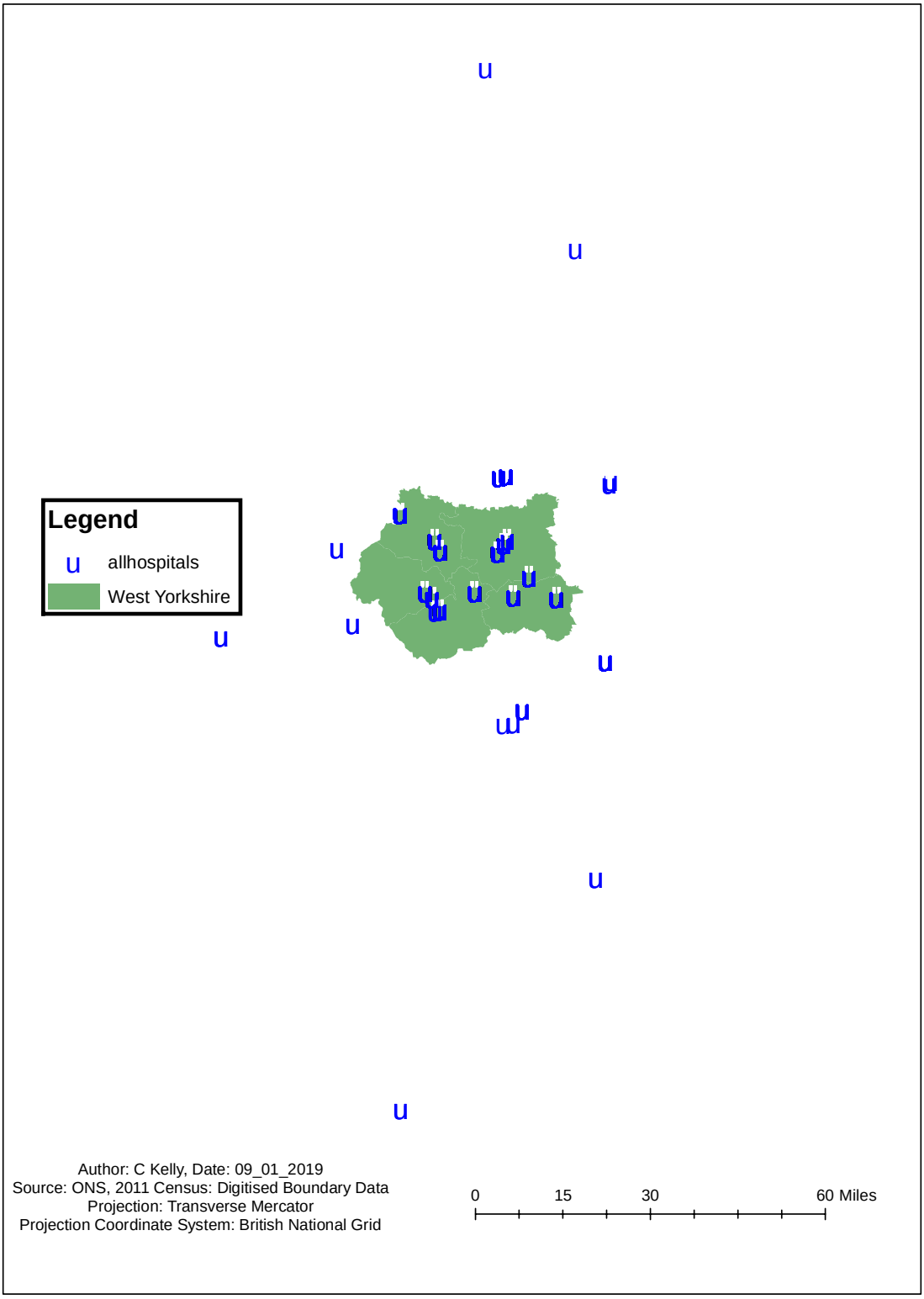
The results showed that there are some key differences between the two patient groups. There are also differences between the health measures results for the two groups. It should be noted

that it is not possible to compare the OHS and the OKS directly as they include slightly differing questions. As is summarized in Table 16 there were statistically significant differences in the health status at both baseline and follow up for the EQ-5D-3L and EQ-5D VAS. With TKR having higher baseline scores and index values, but lower follow up scores. Based on this discussion and the differences between the explanatory variables and health measures a decision was made to analyse the two groups (THR and TKR) separately in the statistical models.

Table 16: Do THR and TKR patients differ?

Characteristics (Numbers in brackets 95% CI around the mean)	Hip Replacement	Knee Replacement	Test (t-test or $\chi 2$)	Sig difference?
Total	4,550	5,506	-	-
Sex (% Male)	40.7%	46.2%	$\chi 2$	p < 0.001 ***
Age (years)	67.81 (67.432 – 68.056)	68.89 (68.547 – 69.027)	t-test	p < 0.001***
Ethnicity (% White British)	88.92%	85.5%	$\chi 2$	p < 0.001***
Index of multiple deprivation score	21.87 (21.493 – 22.352)	23.70 (23.409 – 24.220)	t-test	p < 0.001 ***
Living alone (%)	29.01%	25.50%	$\chi 2$	p < 0.001 ***
Days on Waiting List	77.75	87.95	t-test	p < 0.001 ***
Days in Hospital (95% CI)	5.311 (5.194 – 5.427)	5.489 (5.376 – 5.602)	t-test	p = 0.0219 **
Comorbidities	34.77%	40.62%	$\chi 2$	p < 0.001 ***
Type of Hospital (% NHS provider)	83.43%	85.76%	$\chi 2$	p = 0.274
Hospital Quality(% Good/ Excellent)	43.08%	39.14%	$\chi 2$	p < 0.001 ***
Rural / Urban Location (% urban)	93.19%	93.69%	$\chi 2$	p = 0.393
Travel to the hospital				
Travel time to Hospital (mins)	14.80 (14.72 – 15.23)	14.50 (14.54 – 14.95)	t-test	p = 0.08
Travel Distance to Hospital (km)	11.58 (11.52 – 12.01)	11.36 (11.38 – 11.78)	t-test	p = 0.17
Health Measures				
Baseline EQ-5D-3L (95% CI)	0.325 (0.315 – 0.334)	0.383 (0.376 – 0.392)	t-test	p < 0.001 ***
Follow up EQ-5D-3L (95% CI)	0.764 (0.756 – 0.772)	0.710 (0.70 – 0.72)	t-test	p < 0.001***
Baseline EQ-5D VAS (95% CI)	62.55 (61.89 – 63.18)	65.47 (64.94 – 66.05)	t-test	p < 0.001 ***
Follow up EQ-5D VAS (95% CI	74.26 (73.69 – 74.86)	70.85 (70.31 – 71.43)	t-test	p < 0.001 ***

(Legend * p<0.1, **p<0.05, ***P<0.001)



Map 2: Hospitals attended by patients in WY

3.3.2 Travel time and distances to healthcare facilities

The travel times and distances calculated using the HES data for the THR and TKR patients (combined) are summarized in Table 17 with combinations of:

- LSOA vs home postcode data
- Actual Hospital vs nearest
- Different measures of transport accessibility: straight-line distance (miles), road network distance (miles) , road network travel time (mins) and bus travel time (mins)

It is worth noting that 91 patients in table 17 could not have got to a 10 am appointment by bus using the current bus schedules even if they left by 7am in the morning. These are based on the total sample of 10,056 patients.

Table 17 : A summary of the results allowing comparisons between the different methods of determining the travel times and distances to the hospital appointments

Hospital	Home Location	Method	Straight-Line Distance (miles)	Road Network Distance (miles)	Road Network Travel Time (mins)	Bus Travel Time (mins)
Nearest	LSOA	Average (Range)	2.90 (0.01 – 8.45)	4.19 (0.19 – 14.5)	9.53 (0.91 – 31.76)	26.60 (1.91 – 71.01)
		95% CI	2.87 – 2.93	4.15 – 4.24	9.45 - 9.61	26.44 – 26.88
	Postcode	Average (Range)	2.91 (0.01 – 8.82)	4.44 (0.01 – 16.40)	9.75 (0.96 – 34.20)	26.85 (0.24 – 102.76)
		95% CI	2.88 – 2.91	4.31 – 4.40	9.66 – 9.83	26.64 – 27.11
	LSOA vs Postcode	t-test	P = 0.009**	P<0.001***	P<0.001***	P<0.001***
Attended	LSOA	Average (Range)	5.34 (0.01 – 91.5)	7.25 (0.19 – 115.5)	14.82 (1.26 – 175.54)	44.23 (2.92 – 167.56)
		95% CI	5.26 – 5.41	7.15 – 7.34	14.65 – 14.98	43.76 – 44.70
	Postcode	Average (Range)	5.33 (0.01 – 91.08)	7.25 (0.01 – 115.7)	14.85 (0.10 – 176.0)	44.13 (0.24-170.81)
		95% CI	5.26 – 5.41	7.15 – 7.34	14.75 – 14.98	43.76 – 44.70
	LSOA vs Postcode	t-test	p = 0.388	p = 0.952	p = 0.014**	p<0.001***
Attended vs Nearest	Postcode	t-test	p < 0.001***	p < 0.001***	p < 0.001***	p < 0.001***
	LSOA	t-test	p < 0.001***	p < 0.001***	p < 0.001***	p < 0.001***
Attended & Postcode vs Nearest & LSOA		t -test	p < 0.001***	p < 0.001***	p < 0.001***	p < 0.001***

(Legend * p<0.1, ** p<0.05, ***p<0.001)

Starting with the results focused on distance shown in Table 17. As expected, the straight-line distance calculations are statistically significantly lower than the distances calculated using the road network. On average 2.91 miles compared to 4.44 miles (1.5 miles less) for the home postcode to the nearest hospital and 5.33 miles compared to 7.25 miles for the home postcode to the actual hospital attended (1.92 miles). The 95% CI do not overlap, indicating that there is a statistically significant difference. The results of the t- tests show that there are no statistically significant differences comparing using home postcode or LSOA, to the hospital attended using straight-line distance ($p<0.388$). Under this comparison the results would not differ if only LSOA (population weighted centroid) was available and not home postcode. Statistically significant differences are observed between using straight-line distance to the nearest available hospital compared to the actual hospital attended ($p< 0.001$) and when comparing the most accurate origin and destination (home postcode and hospital attended) and least accurate (LSOA and nearest hospital) ($p < 0.001$). The key aspect that influences the result for the straight-line calculations is in knowing the hospital attended (compared to using the nearest facility).

For distances calculated using the road network there was a statistically significant difference comparing LSOA and home postcode to the nearest facility, but not the actual hospital attended. The results showed a statistically significant difference comparing the nearest vs actual hospital attended and most accurate vs least accurate starting and finishing points (where there was a 3.06 mile difference in the averages). For example, using LSOA and the nearest hospital had an average distance of 4.19 miles compared to home postcode and actual hospital attended with an average distance of 7.25 miles. Again, whilst the starting point (home postcode or LSOA) had a small impact on the results the key influence was the hospital attended and the method using the road network compared to Straight-Line distance.

Calculating travel times using the road network resulted in a similar pattern emerging as with the distance calculations. There was a statistically significant difference between the means comparing the LSOA and home postcode starting points travelling to the nearest hospital and actual hospital attended. There was a statistically significant difference between calculating the LSOA to the nearest facility and home postcode to the actual facility ($p<0.001$), with a difference in the average travel time of 5.32 mins. The key differences occurred in using the travel times calculated using the bus network and schedules. We know that over 25% of households nationally do not have a car (ONS, 2016a) and that if the only driver in the household is having an operation they would have to find an alternative method to travel, as they would not be able to drive back following the operation. The alternatives for travelling to hospital are by private taxi or getting a lift from a family member or friend which would have the same travel times as

the road network travel time, using public transport (e.g. getting a bus) or in the case of hospital treatment the PTS, which could involve picking up multiple passengers. Calculating bus travel times provides a better proxy for the latter two options. Section 5.6 provides an example comparing the different modes of travel to Chapel Allerton Hospital in Leeds.

The results indicate that there are no statistically significant differences in the means when comparing use of LSOA with home postcode to the nearest facility, but that there is a considerable inequality in travel time between travelling using the road network (e.g. by car) and travelling by bus, which takes 2.8 times longer on average. This is even more extreme when comparing the nearest facility to the actual facility attended. On average the travel time would be 44.13 min, with one person travelling just under 3 hours by bus to get to the hospital and ninety-one patients are not be able to get to the hospital by a 10 am appointment if they left at 7 in the morning and used public transport.

The conclusion is that not knowing the actual hospital attended (rather than using the nearest) has the biggest effect on the results. One of the patients who travelled the furthest from their home postcode to the actual hospital where they received their THR, had one of the fastest travel times when it was assumed that they attended the nearest facility. Whilst in some cases using LSOA vs home postcode has a small effect on the results it did not have the same effect of reordering the patients in terms of who lives the furthest away. Results indicate that centralising services to within WY in this geographical location, given the context of choice will have the effect of reducing average travel times for those that have chosen to go out of the WY area for treatment.

One of the other differences noted in the literature is whether there are any statistically significant differences in the travel times for individuals living in urban vs. rural areas. The WY population is predominantly urban, but around 9% (~900) live in what is classified as a rural (as opposed to an urban) area. Table 18 shows the differences in road network and travel times from the home postcode and LSOA to the hospital attended comparing those living in a rural vs. urban location. As expected those living in rural areas had statistically significant longer travel distances and travel times than those living in urban areas. There were statistically significant differences between using the home postcode and LSOA for bus travel times for both urban and rural residential locations. For example, using the home postcode for urban locations the average travel time by bus was 43.17 mins (95% CI 42.71 – 43.61) using the LSOA for urban locations average travel time by bus was 47.73 (95% CI 44.09 – 51.38), so a statistically significant difference in the means. Comparing the rural residential locations bus times compared to urban

using the home postcode average travel times by bus would be 59.16 mins by bus for the rural residences and 43.17 mins for the urban residences.

Table 18: Rural vs Urban Locations (hospital attended)

		Straight-Line Distance	Road Network Distance	Road Network Travel Time	Bus travel time
Home	Rural (range)	6.96 (0.65 – 91.08)	9.51 (0.81 – 109.11)	19.68 (2.04 – 169.12)	59.16 (4.39 – 164.57)
	95% CI	6.55 – 7.27	9.07 – 9.97	18.97 – 20.40	57.06 – 61.26
	Urban (range)	5.22 (0.01 – 90.3)	7.08 (0.01 – 115.7)	14.50 (0.01 – 176)	43.17 (0.24- 170.81)
	95% CI	5.15 – 5.30	6.98 - 7.18	14.33 – 14.66	42.71 – 43.61
LSOA	Rural (range)	6.87 (0.55 – 91.53)	9.51 (0.77 – 109.7)	19.13 (3.09 – 170.46)	59.32 (6.13 – 161.39)
	95% CI	6.51 – 7.23	9.06 – 9.96	`18.40 – 19.85	46.72 – 71.91
	Urban (range)	5.22 (0.211 – 91.53)	7.08 (0.19- 115.5)	14.51 (1.26 – 175.54)	47.73 (2.92 – 167.56)
	95% CI	5.15 – 5.30	6.99 – 7.18	14.34 – 14.67	44.09 – 51.38

3.3.3 Travel times and distances to the GP

This section shows the results of calculating the travel times and distances to the nearest GP. A number of studies in Chapter 2 had identified that it might be the location of the GP practice that is critical, as the gatekeeper to diagnosis and treatment, which is also discussed in articles such as Croft et al. (2011). A comparison of the travel times and road distances to the nearest and registered GP practice are provided in Table 19. A large proportion of the patients were not registered at their nearest (by travel distance) GP. One patient had a home postcode 27 miles from their registered GP. There was a statistically significant difference in the means between the distances that patients would be travelling if they attended their nearest GP compared to the distance from their home location to their registered GP (and the same for travel times). For example, using road network distance to the nearest GP had an average distance of 0.88 miles (95% CI 0.86 – 0.89), whereas to the registered GP the distance was on average 1.55 miles (95% CI 1.52 – 1.57).

Table 19: Travel times and distances to the GP (THR and TKR) – Home Postcode to the nearest and registered GP

			Road Network Distance	Road Network Travel Time
Nearest	Home postcode	Average (range)	0.88 miles (0 – 7.0 miles)	2.51 mins (0 – 19.75 mins)
		95% CI	0.86 – 0.89	2.48 – 2.53
Registered GP	Home Postcode	Average (range)	1.55 miles (0 – 27.49)	4 mins (0 – 49.46)
		95% CI	1.52 – 1.57	4.21 – 4.33

3.3.4 Differences between TKR and THR patients?

For the analyses it is interesting to see whether there are any differences between the distances and travel times that THR and TKR patients are travelling. A summary is provided in Table 20, where on average THR patients were travelling further, but there was no statistically significant differences found in the means. The conclusion for this sample of patients is that there is no systematic differences in the distances and travel times travelled for this population of THR and TKR patients to the hospital either using the home postcode or LSOA as the starting point.

Table 20: THR Patients vs TKR Patients (Home postcode and LSOA to the hospital attended)

			Straight-Line Distance (miles)	Road Network Distance (miles)	Network Travel Time (mins)	Bus travel time (mins)
Home Postcode	THR Patients	Average (Range)	5.38 (0.07 – 91.08)	7.31 (0.15 – 115.7)	14.98 (0.78 – 175.99)	43.89 (1.68 – 170.81)
		95% CI	5.26 – 5.50	7.16 – 7.46	14.72 – 15.23	43.23 – 44.57
	TKR Patients	Average (Range)	5.30 (0.01 – 81.14)	7.20 (0.01 – 104.19)	14.74 (0.10 – 170.78)	44.31 (0.24 – 168.03)
		95% CI	5.20 – 5.39	7.07 – 7.32	14.54 – 14.95	43.71 – 44.91
LSOA	THR Patients	Average (Range)	5.36 (0.17 – 91.33)	7.29 (0.19 – 115.25)	14.96 (1.26 – 175.53)	44.11 (2.92 – 163.19)
		95% CI	5.25 – 5.50	7.13 – 7.44	14.71 – 15.21	(43.39 – 44.81)
	TKR Patients	Average (Range)	5.29 (0.13 – 80.79)	7.181 (0.27 – 103.62)	14.70 (1.278 – 170.82)	44.33 (3.17 – 167.56)
		95% CI	5.19 – 5.39	7.06 – 7.30	14.49 – 14.91	(43.69 – 44.97)

3.3.5 How easy do THR and TKR patients find it to walk and get into vehicles?

The analysis of the individual questions on how easy patients find it to walk and how easy is it to get into a vehicle, which are two of the 12 questions in the OHS and OKS are summarized in Table 21. This provides a summary of the responses at baseline (completed before the operation) and at follow up (completed six months following the operation) to these two questions. Whilst we do not know how patients have travelled (e.g. car / bus) it can be seen from the baseline data and to some degree the follow up data that the burden of travelling to the hospital or GP could be quite significant for some patients. The act of walking to the car/ from a car park to the hospital or even in getting into a vehicle is problematic and stressful. For the THR patients 37.1% stated either that they could not walk at all or only around the house before the operation compared to 30.1% of knee patients. Prior to the operation very few < 2% reported that it was impossible to get into a vehicle, but 34.7% of THR patients and 27.1% of TKR patients reported that it was very difficult. These two factors (getting into a vehicle and walking) alone show that a large percentage of patients would have problems travelling to healthcare prior to the operation and some still having issues with walking and getting into vehicles following the THR or TKR operation.

Table 21: Problems with walking and using vehicles at baseline and follow up (%)

		Hip Replacements		Knee Replacements	
		Baseline	Follow up	Baseline	Follow up
Problems walking	Not at all	17.7%	2.6%	13.9 %	4.3%
	Around the house only	19.4%	5.2%	16.2 %	5.5%
	5 – 15 mins	32.9%	10.0%	39.3 %	14.1%
	16 – 30 mins	22.2%	18.7%	23.0 %	23.6%
	No pain/ more than 30 mins	7.8%	63.6%	7.4 %	52.4%
Problems getting into/ out of a vehicle	Impossible to do	1.5%	0.3%	0.9%	0.4%
	Extremely difficult	34.7%	3.4%	27.1%	6.7%
	Moderate trouble	49.4%	17.2%	50.7%	27.4%
	Very little trouble	11.2%	32.4%	15.4%	33.8%
	No trouble at all	3.2%	46.7%	5.9%	31.6%

Comparing the levels of mobility following the operation between THR and TKR patients – a higher percentage of THR patients (63.6%) had no pain or could walk more than 30 minutes following the operation compared to the TKR patients (52.4%). THR patients are also more likely to report no trouble getting out of/ into a car 6 months following the operation than TKR patients. The data describes a mixed picture with inequalities in both baseline and follow up being evidenced in terms of walking and ease of getting into a vehicle. TKR patients on average find it easier than THR patients to both walk and get into vehicles prior to the operation, but this trend is reversed following the operation, with THR patients on average having better mobility after 6 months.

3.3.6 Health outcomes for patients undergoing a THR or TKR

A summary of the health outcomes for the HES-PROMS patient population by THR and TKR are provided next. These are considered in the order of Table 22 and also consider an assessment of the level of missing data.

Table 22: Health and Proxy Health Measures

Dataset	Measure	Use	Range/ scale
PROMS	EQ-5D-3L	Generic	- 0.594 – 1.0
	EQ-5D VAS	Generic	0 – 100
	General Health	Generic	Excellent, Very Good, Good, Fair, Poor
	Oxford Hip Score	THR	0 – 48
	Oxford Knee Score	TKR	0 – 48
HES	Length of Stay	Generic	Days
	DNA	Generic	Attended/ DNA

3.3.6.1 EQ-5D-3L

The result of the EQ-5D-3L index values are summarized for the THR patients at baseline in Figure 14 and follow up in Figure 15. It can be seen that the values at the baseline span from the lowest -0.549 (worse level of health) up to 1. It should be expected that given that these patients are having a THR that they would not be in full health (1) at baseline, but if the operation has been a success that there would be improvements at follow- up. Some patients can be seen to have values < 0 both at baseline and follow up, which are states of health that are considered worse than death.

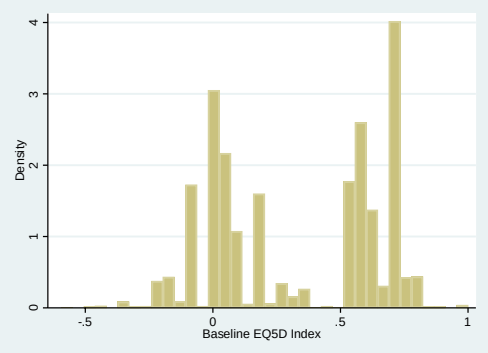


Figure 14: Baseline EQ-5D-3L (THR)

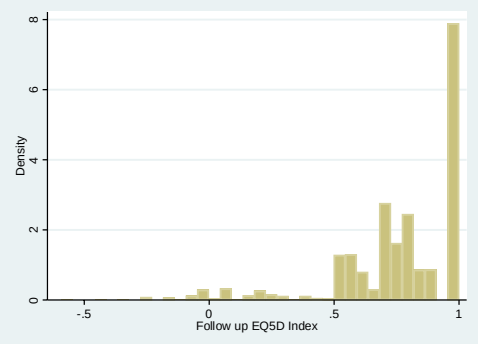


Figure 15: Follow up EQ-5D-3L (THR)

The index values for the TKR patients are shown at baseline (before the operation) in Figure 16 and follow up in Figure 17. The distributions again show the full range of index values from -0.549 (extreme problems on all 5 categories) up to 1 (full health).

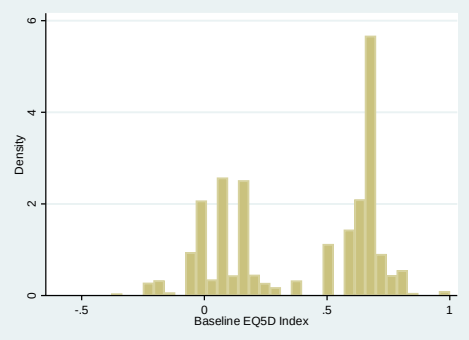


Figure 16 Baseline EQ-5D-3L (TKR)

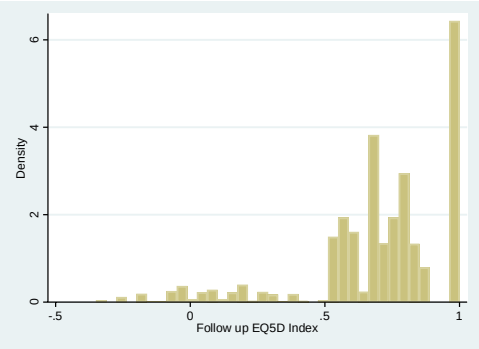


Figure 17 Follow up EQ-5D-3L (TKR)

As expected in both subgroups (THR and TKR) there are a range of index values at baseline ranging from 1 (full health) to -0.549 (worse level of health state possible). For the THR patients the average index score was 0.325 (95% CI of 0.315 – 0.334) and for the TKR patients 0.385 (95% CI 0.376 – 0.392) at the baseline. This shows as a statistically significant difference between the means at the 95% CI, with the THR patients having baseline scores at a lower level (worse) than the TKR patients. This rises to 0.76 (95% CI 0.756 – 0.772) for the THR and 0.71 (95% CI 0.70 – 0.72) for the TKR in the follow up, which is also statistically significantly different at the 95% CI. Whilst patients undergoing THR have on average worse baseline scores compared to the TKR patients they on average have higher scores six months following the operation. For this study the key interest is whether the differences within these subgroups (THR and TKR) are associated in any way with differences in travel times and distances to healthcare facilities.

Parkin et al. (2016) and Devlin (2016) argue that analysing data changes at the domain level or assessing whether the index scores improve, do not change, worsen or experience a mixed change (the score for one domain goes up and another down) provides a better

representation of the changes in distributions. Using this description 90.42% of THR patients had higher EQ-5D-3L index scores following the operation compared to 84% of TKR patients. The same domain information as input into the index values (minus the tariff values), is presented in *Table 23* and *Figure 18* for the THR patients. Forty-two percent of THR patients reported extreme problems in the domain of pain/ discomfort and 19% in the domain of undertaking usual activities, with only 0.25% of patients stating that they had extreme problems with mobility in the pre operation data Following the operation 73% of patients improved in the pain/ discomfort domain (either from extreme to some or some to no pain). For the assessment of anxiety and depression 5% of the patients reported a worsening following the operation. There is also evidence of variation between patients in terms of how much improvement there was.

Table 23: Summary of change in SAH health by domain following the THR

	Mobility	Self-Care	Usual Activities	Pain/ Discomfort	Anxiety/ Depression
CHANGE					
No Change	1,538 (47.00%)	1,919 (58.65%)	1,280 (39.12%)	858 (26%)	2,113 (64.58%)
Worse	36 (1.10%)	115 (3.51%)	115 (3.51%)	33 (1.00%)	194 (5.98%)
Better	1,698 (51.89%)	1238 (37.83%)	1,877 (57.36%)	2381 (73%)	965 (29.49%)

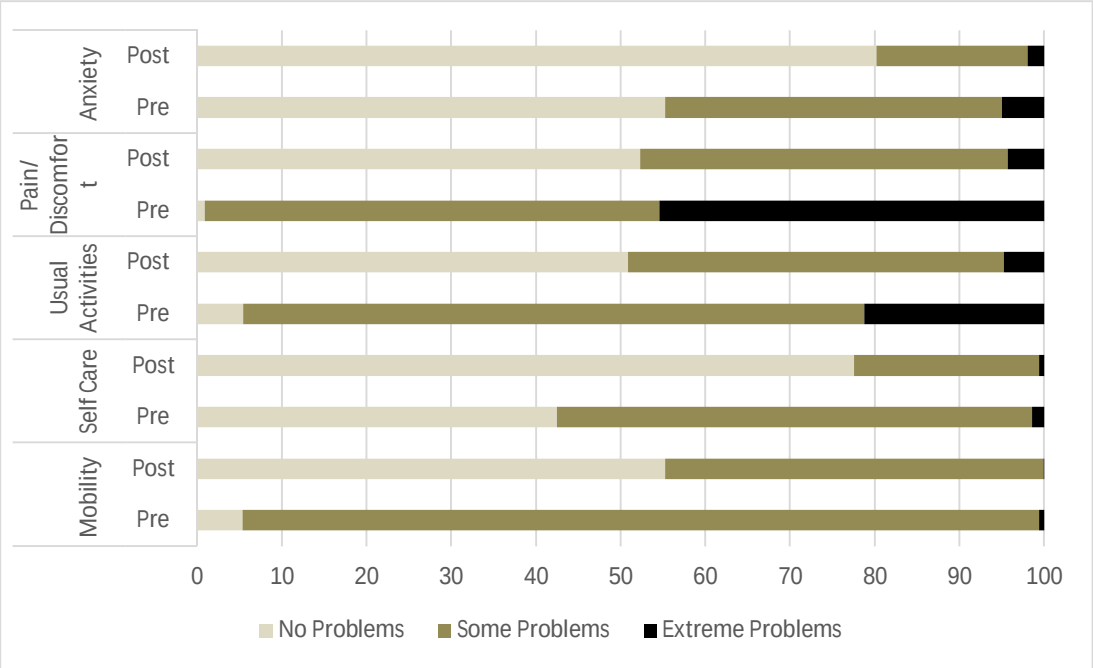


Figure 18: THR patients: Scores against domains pre and post operation (%)

As with the THR patients the majority (98%) of the TKR patients reported that they had some or extreme problems with pain prior to the operation, 6.3% reported extreme problems with pain and 59.8% some problems with pain and discomfort six months following the operation (see Figure 19). Again a wide range of differing responses within this subgroup can be found.

Interestingly only a very small percentage of the TKR and THR patients reported extreme problems in the mobility domain before and after the operation. This would seem a strange result given the impact on mobility that leads patients to require a THR or TKR. The answer may lie in the description of the mobility domain, which allows patients to answer that they have no problems in walking about, some problems in walking about or are confined to bed. The majority as shown in Figure 19 (TKR patients) reported some problems in walking. There is a big difference (and degrees of difficulty) between some problems and a very definite answer of being confined to bed. The 3 level domains might not pick up some of the subtleties that are key to patients undergoing THR and TKR. A newer 5 level question is now available which has 5 levels to each of the domains (Herdman et al., 2011), so could potentially pick up some of these changes better). This newer version was not available for this study.

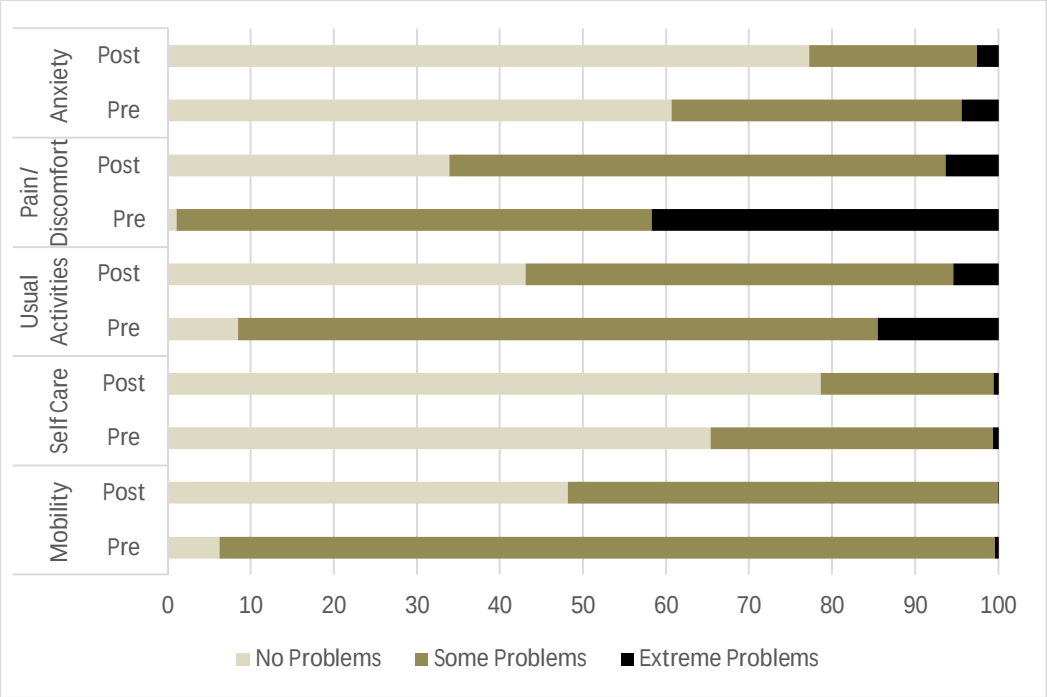


Figure 19: TKR patients: Scores against domains pre and post operation (%)

One of the key aspects that the study is interested in is whether differences in travel times and distances to healthcare facilities are associated with differences in the change in EQ-5D-3L index values (follow up minus baseline) and whether patients would notice the difference. Figure 20

shows the distribution of change in scores for the THR patients. The average change was 0.416 (CI 95% 0.405 – 0.427) (an improvement). The TKR scores are shown in Figure 21 whereby the average change was 0.305 (95% CI 0.295 – 0.315) (an improvement). These average improvements are above the MCID of 0.074 for EQ-5D-3L, so indicating that the majority of patients would notice the difference.

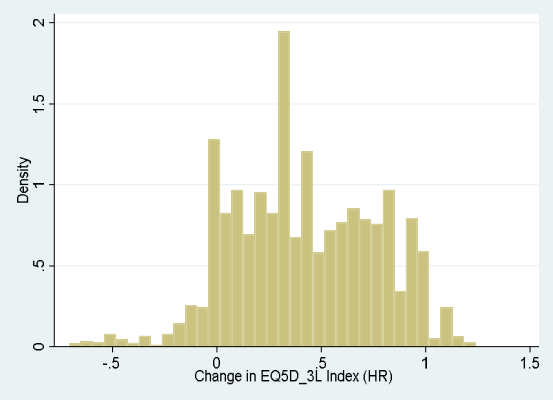


Figure 20: Change in EQ-5D-3L index (Follow up – Baseline) THR

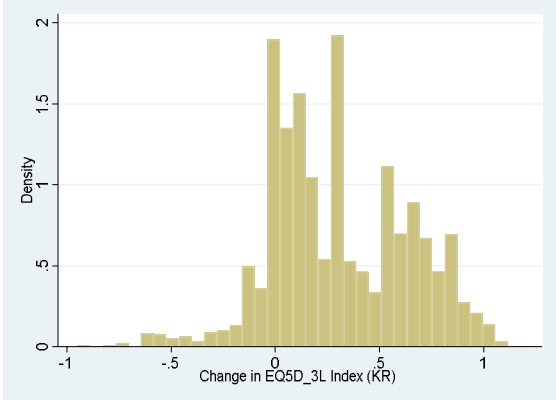


Figure 21: Change in EQ-5D-3L Index (Follow up – Baseline) TKR

3.3.6.1.1 EQ-5D-3L Missing data assessment

The level of missing missing data across the complete THR and TKR sample is shown in Figure 22. This graph splits the data into follow up and baseline data with the black rectangles representing the missing data. This figure shows that there is a small number of baseline data that is missing with also missing follow up data (black line at the right hand side), a larger proportion with missing baseline data, but complete follow up data and then a larger proportion with missing follow up data, but complete baseline data (large black rectangle).

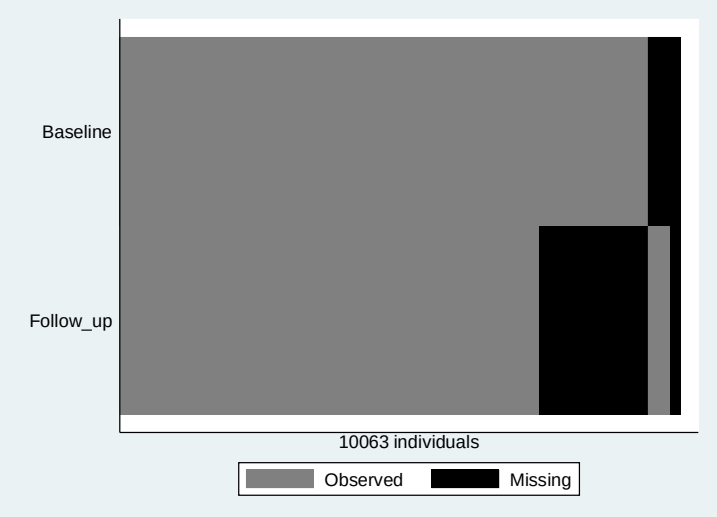


Figure 22: Missing data index level (THR and TKR combined)

The key issue then is whether there are any systematic differences between those with complete data and those with missing EQ-5D-3L domain values. For the THR patients a summary of the complete data vs. missing data assessment is shown in Table 24 and for the TKR patients the same assessment is provided in Table 25. It is assumed that there is a statistically significant difference where p<0.05. For the THR patients there was a statistically significant difference by age, where the younger the patient was the more likely it was that the data was incomplete. Also, the higher the index of multiple deprivation score (more deprived) the greater the likelihood that the data was incomplete, as was living alone, increased days in hospital and having comorbidities. There was no statistically significant difference based on the travel time or distance to the hospital.

For the TKR sample, being female, non-white British, living in an area with a higher derivation score, living alone, spending more days in hospital post operation, attending a hospital that "requires improvement", and living closer to the hospital where the operation took place both in terms of travel time and distance led to being more likely that you would not have complete data. Based on this discussion it would seem a valid course of action to undertake the analysis both with and without missing data imputed.

Table 24: Comparison of THR patients with and without missing data for EQ-5D-3L

Characteristics (number in brackets = standard deviation)	Complete baseline and follow up	Incomplete baseline/ follow up	t-test or χ 2 test	Statistically significant difference?
Total	3,404	1,146		
Sex (% Male)	40.69%	40.84%	χ 2	p = 0.929
Age (years)	68.02 (10.64)	67.19 (12.43)	t-test	p = 0.029**
Ethnicity (% White British)	88.75	89.44	χ 2	p = 0.518
Deprivation	21.16 (14.98)	23.97 (15.75)	t-test	p<0.000***
Living alone (%)	28.23%	31.33%	χ 2	p = 0.046**
Days on Waiting List	77.39 (58.83)	78.84	t-test	p= 0.473
Days in Hospital	5.20 (4.09)	5.65 (4.25)	t-test	p = 0.001**
Comorbidities	67.7%	58%	χ 2	p <0.001***
Type of Hospital (% NHS provider)	82.99%	84.73%	χ 2	p = 0.171
Hospital Quality (% Good/Outstanding)	43.8%	40.92%	χ 2	p = 0.089*
Rural / Urban Location (% Urban)	92.92%	93.02%	χ 2	p = 0.910
Travel time to Hospital (mins)	14.85 (9.13)	14.65 (9.49)	t-test	p = 0.5144
Travel Distance to Hospital (kms)	11.6km (8.95)	11.4km (9.17)	t-test	p = 0.4836

(Legend *p<0.1, **p<0.05, *** p<0.001)

Table 25: Comparison of TKR patients with and without missing data for EQ-5D-3L

Characteristics (number in brackets = standard deviation)	Complete baseline and follow up	Incomplete baseline/ follow up	t-test or χ 2 test	Statistically significant difference?
Total	4134	1372		
Sex (% Male)	47.33%	42.86%	χ 2	p = 0.004**
Age (years)	68.96 (9.08)	68.67 (10.18)	t-test	p = 0.3129
Ethnicity (% White British)	86.57%	82.36%	χ 2	p <0.001***
Deprivation	22.90 (15.50)	26.13 (16.56)	t-test	p<0.001***
Living alone (%)	24.58%	28.28%	χ 2	p =0.006**
Days on Waiting List	87.58 (68.60)	89.06 (70.49)	t-test	p = 0.502
Days in Hospital	5.28 (3.38)	6.20 (6.87)	t-test	p < 0.000***
Comorbidities (<1 comorbidity)	60.49%	55.97%	χ 2	p = 0.003**
Type of Hospital (% NHS provider)	85.70%	85.93%	χ 2	p = 0.833
Hospital Quality (% Good/Outstanding)	40.11%	36.22%	χ 2	p = 0.011**
Rural / Urban Location (% Urban)	93.4%	94.24%	χ 2	p = 0.280
Travel time to Hospital (mins)	14.7km (8.06)	13.87km (7.65)	t-test	P< 0.001***
Travel Distance to Hospital (kms)	11.5km (7.7)	10.8km (7.3)	t-test	P< 0.001***

(Legend *p<0.1, **p<0.05, *** p<0.001)

3.3.6.2 EQ-5D VAS

The distribution of the EQ-5D VAS score for the THR patients are provided in Figure 23(baseline) and 24 (follow up). The average score was 62.54 prior to the operation (range 0 – 100) and 95% CI 61.89 – 63.18. At 6 months post operation the average score had increased to 74.28 (range 0 – 100) and 95% CI 73.69 – 74.86, so an overall improvement following the operation.

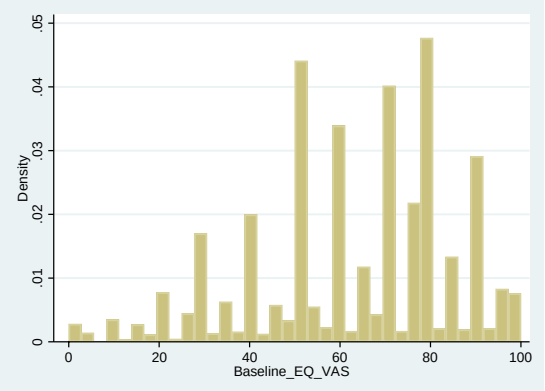


Figure 23: Baseline EQ-5D VAS (THR)

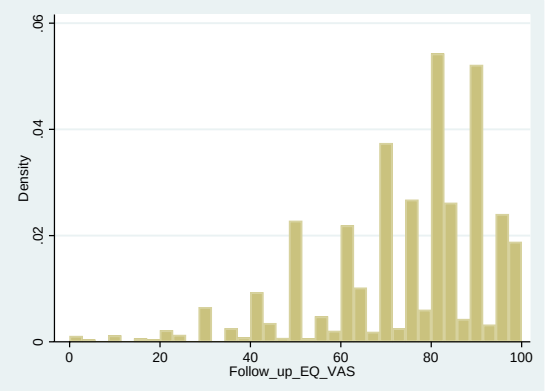


Figure 24: Follow up EQ-5D VAS (THR)

The distribution of the EQ-5D VAS scores for the TKR patients are provided in Figures 25 (baseline) and 26 (follow up). The average baseline score was higher for the TKR patients at 65.49 (range

0 – 100) and 95% CI of 64.94 – 66.05. At 6 months post operation the average score had increased to 70.87 (range 0 – 100) and 95% CI 70.31 – 71.43 for the TKR patients.

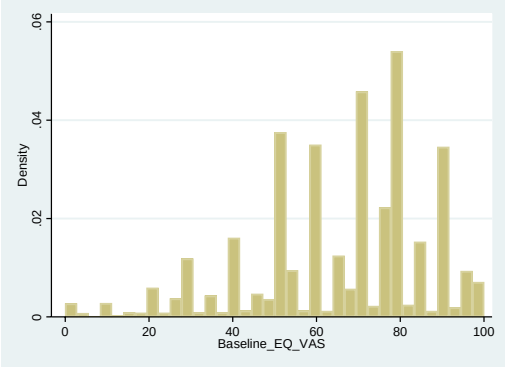


Figure 25: Baseline EQ-5D VAS (TKR)

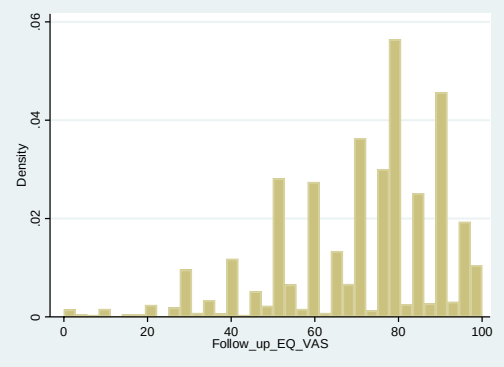


Figure 26: Follow up EQ-5D VAS (TKR)

There was a statistically significant difference in the mean scores at baseline and follow up between the THR and TKR patients. In total 72.79% of the THR patients had an improvement in their score (8% stayed the same and 19% had a worsening of score). For the TKR patients, 66% had an improvement in score, with 24% reporting a worsening and 9% the same score pre and post operation. A larger number of TKR patients than THR patients reported that their health state at 6 months was worse than at baseline (pre–operation). The distribution of change in EQ-5D VAS scores are shown in Figure 27 (THR) with a mean of 10.58. The equivalent distribution for the TKR patients is shown in Figure 28. The average change was 4.06 (CI 95% 3.43 – 4.70).

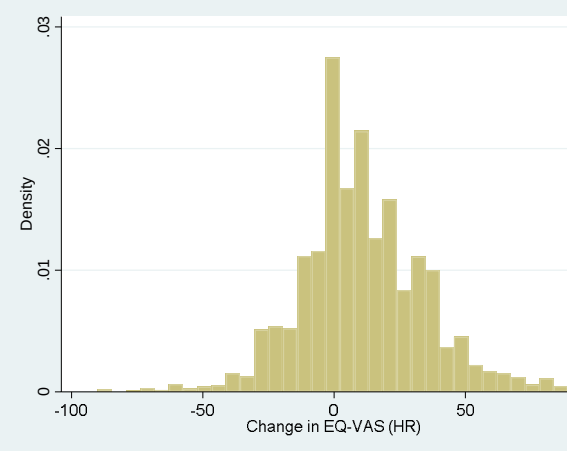


Figure 27: Change in EQ-5D VAS score for THR

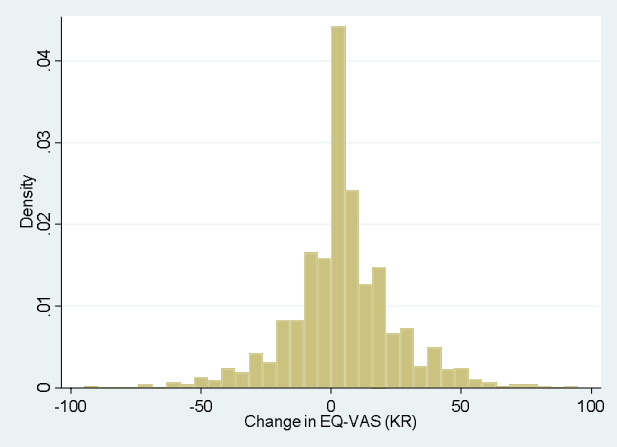


Figure 28: Change in EQ-5D VAS score for TKR

3.3.6.2.1 EQ-5D VAS : Missing Data Assessment

The results showing missing data for the EQ-5D VAS, are shown in Figures 29 (THR) and 30 (TKR). They show a similar pattern to the EQ-5D-3L results, where there is less missing data for the TKR patients than THR patients. In both cases there are a smaller proportion of the patients with missing baseline and missing follow up data. The missing data graphs in Figure 29 and 30 show that there are a number of variables that could be predictors for missing data for the EQ-5D VAS. The THR patients (Table 24) answering the EQ-5D VAS question were if they lived in a more deprived area, had more comorbities, lived alone, and spent more days in hospital. For the TKR patients (some of the variables differed. Predictors of having missing data were being non-white British, living in a more deprived area living alone, having a greater number of longer days in hospital, and living closer (shorter travel times / distance) to hospital.

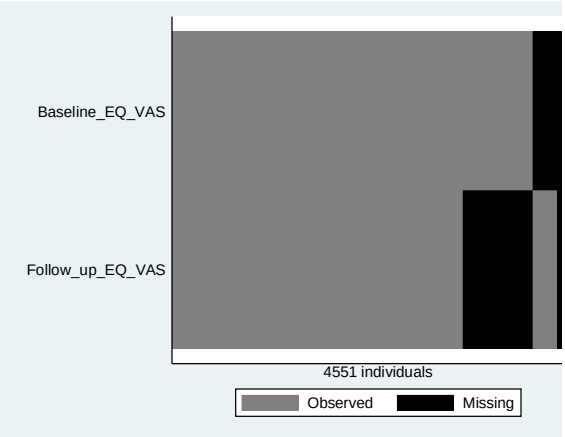


Figure 29: EQ-5D VAS Missing Data (TKR)

Figure 30 EQ-5D VAS Missing data (THR)

Table 26: Comparison of THR patients with and without missing data for EQ-5D VAS

Characteristics (number in brackets = standard deviation)	Complete baseline and follow up	Incomplete baseline/ follow up	t-test or χ 2 test	Statistically significant difference?
Total	3331 (73.2%)	1219		
Sex (% Male)	41.01%	39.95%	χ 2	p = 0.520
Age (years)	67.92 (10.65)	67.51 (12.33)	t-test	p = 0.2683
Ethnicity (% White British)	88.83%	89.12%	χ 2	p = 0.520
Deprivation	20.90 (14.78)	24.51 (16.08)	t-test	p < 0.001 ***
Living alone (%)	27.71%	32.57%	χ 2	p = 0.001 **
Days in hospital	5.17 (3.87)	5.68 (4.77)	t-test	p < 0.001 ***
Days on the waiting list	77.19 (58.11)	79.29 (54.13)	t-test	p = 0.2860
Comorbidities (<1 comorbidity)	67.37%	59.39%	χ 2	p < 0.001 ***
Type of Hospital (% NHS provider)	83.46%	83.34%	χ 2	p = 0.929
Hospital Quality (% Good/Outstanding)	43.02%	43.23%	χ 2	p = 0.898
Rural / Urban Location (% Urban)	92.70%	93.60%	χ 2	p = 0.296
Travel time to Hospital (mins)	14.88 (9.13)	14.57 (8.53)	t-test	p = 0.2941
Travel Distance to Hospital (kms)	11.7km (8.98)	11.4km (8.1)	t-test	p = 0.3208

(Legend *p<0.1, **p<0.05, *** p<0.001)

Table 27: Comparison of TKR patients with and without missing data for EQ-5D VAS

Characteristics (number in brackets = standard deviation)	Complete baseline and follow up	Incomplete baseline/ follow up	t-test or χ 2 test	Statistically significant difference?
Total	4009	1497		
Sex (% Male)	47%	44.02%	χ 2	p = 0.045 **
Age in years	68.15 (9.17)	69.15 (9.87)	t-test	p = 0.2130
Ethnicity (% White British)	87.00%	81.56%	χ 2	p < 0.000***
Deprivation	22.81 (15.30)	26.11 (16.95)	t-test	p <0.000 ***
Living alone (%)	24.4%	28.32%	χ 2	p = 0.003 **
Days on Waiting List	88.09 (68.65)	87.55 (70.24)	t-test	p = 0.8031
Days in Hospital	5.31 (3.43)	6.03 (6.59)	t-test	p <0.001 ***
Comorbidities (<1 comorbidity)	60.2%	57.04%	χ 2	p = 0.032 **
Type of Hospital (% NHS provider)	85.67%	86.04	χ 2	p = 0.719
Hospital Quality (% Good/Outstanding)	39.56%	38.09%	χ 2	p = 0.294
Rural / Urban Location (% Urban)	93.56%	93.79%	χ 2	p = 0.763
Travel time to Hospital mins	14.69 (8.0)	13.98 (7.85)	t-test	p = 0.0032 **
Travel Distance to Hospital (kms)	11.5km (7.6)	10.9km (7.6)	t-test	p=0.0069 **

(Legend *p<0.1, **p<0.05, *** p<0.001)

3.3.6.3 Self- Reported General Health

The summary of responses for the THR and TKR (baseline and follow up) for general health are shown in Figure 31. A larger number of patients are putting themselves into the category of Excellent and Very Good in the post operation phase. There are differences between the THR and TKR classification with THR patients more likely to put themselves in a better category after

the operation than TKR patients. Key for the statistical models is that there is variation in health classification.

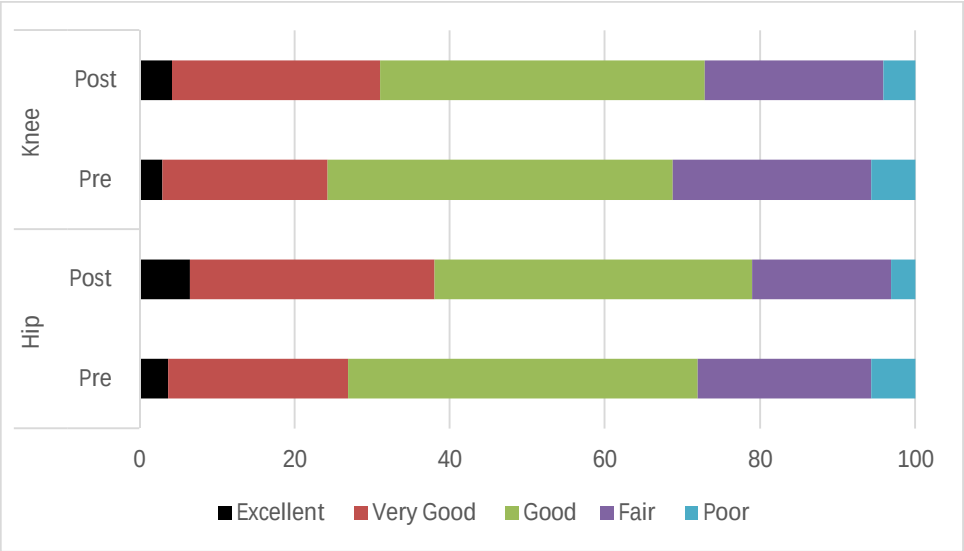


Figure 31: Self-Reported General Health pre and post operation (THR and TKR)

It is interesting to note that there is little difference in the patients' assessment pre and post operation for the General Health measure, overall. This is also shown when looking at the change in General Health (did it get worse, stay the same or improve). For the THR patients 48.9% reported no change, 18.1% a worse classification and 33.0% reported an improvement. For the TKR patients 53.1% reported no change, 26.7% an improvement and 20.2% worse self-reported General Health. As we have seen for the other health measures TKR patients are reporting less improvement pre-operation to post operation than the THR patients. There is therefore a range of responses, as shown in the previously discussed health measures not all patients reporting an improvement in General Health following the operation.

3.3.6.4 Oxford Hip Score (OHS) and Oxford Knee Score (OKS)

The three previous measures discussed (EQ-5D-3L, EQ-5D VAS and Self-Reported General Health) were all generic measures (could be applied to a range of disease groups). The results of the disease specific OHS (applied to the THR) and OKS (applied to the TKR) are presented next.

Using the results from these questions the distributions of the OHS at baseline and follow up are shown in Figures 32 and 33. At baseline the THR patient's average score was 17.27 (95% CI 17.04 – 17.50) and no patients had a maximum score of 48. Following the operation this increased to 37.96 (95% CI 37.67 – 38.26). It should be noted however that there is still variation in the change in scores; not everyone saw an improvement, and for those who did, the magnitude of change varied.

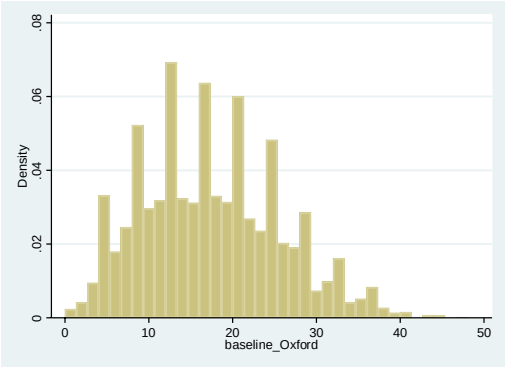


Figure 32: Baseline OHS

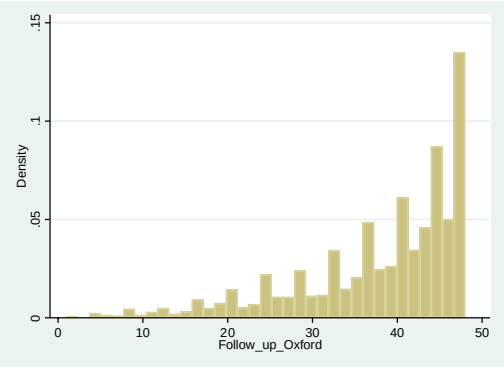


Figure 33: Follow up OHS

The distributions of the OKS for the TKR patients are provided in Figures 34 (baseline) and 35 (follow up). They show a similar pattern to the OHS. On average as with the EQ-5D-3L and EQ-5D VAS scores the pre operation OKS were higher than the THR equivalent 18.10 (95% CI 17.90-18.29), but the post operation scores were on average lower than the OHS at 33.98 (C95% CI 33.69 – 34.27) , but are not comparable due to being based on differing questions and populations.

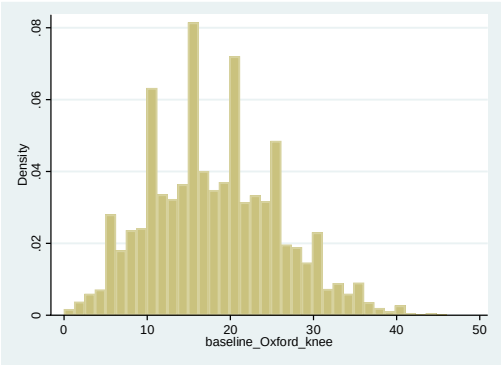


Figure 34: Baseline OKS

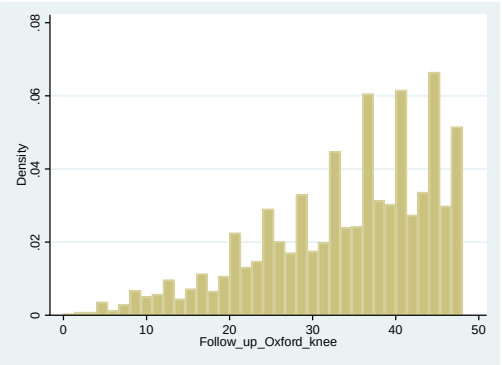


Figure 35: Follow up OKS

The study is interested in these distributions, but also in the change in score following the operation. The distribution of the change in score for OHS is reproduced in Figure 36 and for OKS in Figure 37. For those patients who underwent a THR the average change in OHS was 20.166 (95% CI 19.854 – 20.4678). Indicating that whilst the majority of patients showed an improvement higher than the MCID of 5) there was a large range (-19 to + 45) of outcomes. For those patients who underwent a TKR the average change in the OKS was 15.36 (95% CI 15.079 – 15.645). This is a lower gain that the THR, but showed a similar range of values (-21 to + 46).

As can be seen in Figures 36 and 37 the distribution of change in score broadly follows a normal distribution. With more patients reporting a decline in health for OKS than for OHS following the operations.

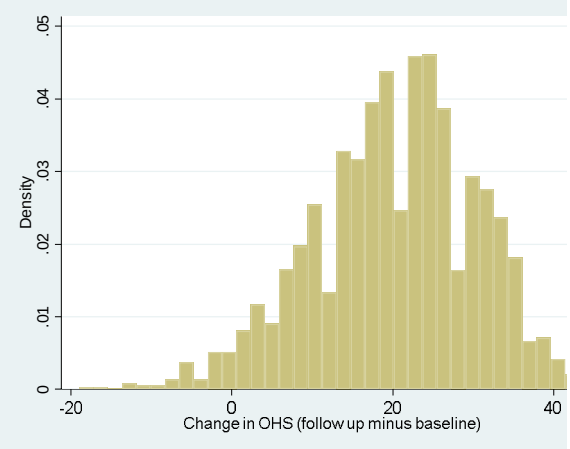


Figure 36: Change in OHS following the THR (operation)

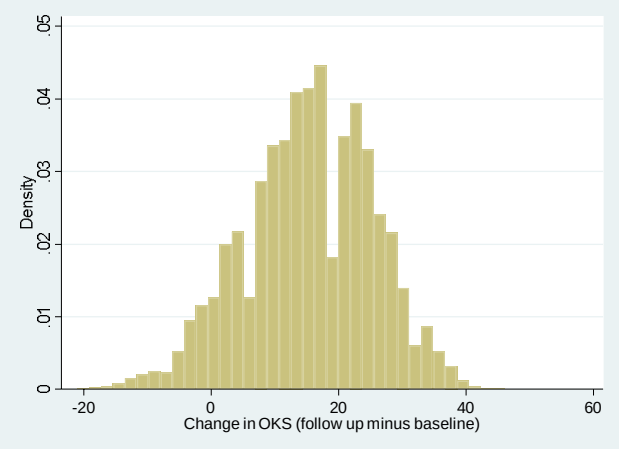


Figure 37: Change in OKS following the TKR operation

3.3.6.4.1 OHS/ OKS: Missing Data

Compared to the generic measures of EQ-5D-5L and EQ-5D VAS the OHS and OKS had less missing data. This could be due to the relevance of the questions that were being asked, which were very specific to either THR or TKR. For the OHS and OKS the results of the missing baseline and follow up data are shown in Tables 28 and 29. The predictors of missing OHS results were being younger, living in a higher deprivation area, living alone, more days in hospital following the operation, more comorbidities, attending a NHS hospital, attending a hospital of lower quality, living in an urban location.

Table 28: Comparison of patients with and without missing data for OHS

Characteristics (number in brackets = standard deviation)	Complete baseline and follow up	Incomplete baseline/ follow up	t-test or χ 2 test	Statistically significant difference?
Total	4,045	810		
Sex (% Male)	39.85	43.33	χ 2	P = 0.065*
Age (years)	68.20 (10.65)	65.86 (13.07)	t-test	p < 0.001 ***
Ethnicity (% White British)	88.89%	89.14%	χ 2	p = 0.837
Deprivation	21.12 (14.87)	25.61 (16.36)	t-test	p < 0.001 ***
Living alone (%)	28.39%	32.06	χ 2	p = 0.041 **
Days on Waiting List	77.12 (57.7)	80.97 (53.72)	t-test	p = 0.1018
Days in Hospital	5.21 (3.96)	5.82 (4.88)	t-test	p < 0.001 ***
Comorbidities (<1 comorbidity)	66.85%	57.20%	χ 2	p < 0.001 ***
Type of Hospital (% NHS provider)	82.83%	86.39%	χ 2	p = 0.016 **
Hospital Quality (% Good/Outstanding)	43.79%	39.53%	χ 2	p = 0.030 **
Rural / Urban Location (% Urban)	92.74%	93.98%	χ 2	p = 0.030 **
Travel time to Hospital (mins)	14.85 (9.01)	14.55 (8.81)	t-test	p = 0.4144
Travel Distance to Hospital (kms)	11.6km (8.8)	11.4km (8.4)	t-test	p = 0.4520

(Legend *p<0.1, **p<0.05, *** p<0.001)

For the OKS 27% of the data was missing (Table 29). The key predictors of having missing data were, being younger, being non-white British, living in a more deprived area, living alone, more days in hospital, more comorbidities, attending a lower quality rated hospital, living closer to the hospital attended.

Table 29: Comparison of patients with and without missing data for OKS

Characteristics (number in brackets = standard deviation)	Complete baseline and follow up	Incomplete baseline/ follow up	t-test or χ 2 test	Statistically significant difference?
Total	4,537	969		
Sex (% Male)	46.28%	45.92%	χ 2	p = 0.837
Age (years)	69.16 (9.12)	67.65 (10.36)	t-test	p < 0.001 ***
Ethnicity (% White British)	86.55%	80.70%	χ 2	p < 0.001 ***
Deprivation	23.07 (15.61)	26.65 (16.51)	t-test	p <0.001 ***
Living alone (%)	25.04%	27.66%	χ 2	p = 0.090 *
Days on Waiting List	87.38 (68.37)	90.58 (72.28)	t-test	p= 0.2053
Days in Hospital	5.36 (3.50)	6.22 (7.63)	t-test	p <0.001 ***
Comorbidities (<1 comorbidity)	60.39%	54.59%	χ 2	p = 0.001 **
Type of Hospital (% NHS provider)	85.70%	86.07%	χ 2	p = 0.763
Hospital Quality (% Good/Outstanding)	39.87%	35.71%	χ 2	p = 0.016 **
Rural / Urban Location (% Urban)	93.48%	94.32%	χ 2	p = 0.327
Travel time to Hospital (mins)	14.61 (7.68)	13.98 (9.19)	t-test	p = 0.0245 **
Travel Distance to Hospital (kms)	11.45km (7.3)	10.91km (8.9)	t-test	p = 0.0476 **

(Legend *p<0.1, **p<0.05, *** p<0.001)

3.3.6.5 Length of Stay (LoS)

The thesis wanted to assess how long patients were staying in hospital following their THR or TKR. Focusing on the THR patients the average LoS in hospital was 5.31 days (95% CI 5.194 – 5.427) and TKR patients 5.49 (CI 95% 5.376 – 5.602). At the 95% CI level there were no statistically significant differences in the LoS in days between the THR and TKR patients. There was a large range in the number of days stayed in hospital. This study is interested in whether travel time or distance to the hospital is associated with differences in LoS for the patients.

3.3.6.6 Missing Appointments

Over the time frame of the study 2009/10 to 2011/12 there were 231,769 outpatient appointments for patients with a recorded OA diagnosis and 23,636 outpatient appointments for patients with an RA diagnosis. A summary is provided in Table 30, with the different categories of attendance. The majority of outpatient appointments were attended. For OA patients 84.53% of the outpatient appointments were attended by the patients and for RA patients 79.90% were attended. Reasons for not attending included that the hospital

had cancelled the appointment or rearranged it, the patient had cancelled the appointment, the patient had just not attended, or that they attended late and were not seen. Out of the 170,886 outpatient appointments for patients with a diagnosis code of OA over 14,000 (5.13%) were missed by patients who did not attend and did not cancel. Out of the 29,582 outpatient appointments for the RA patients 2,326 (7.85%) were not attended and not cancelled by the patients. This is the measure to be included in the logit models 0 = attended and 1 = not attended.

Table 30: Missed Inpatient Appointments

Attendance recorded	Appointments for patients with an OA diagnosis	Appointments for patients with an RA diagnosis
Attended	231,769 (84.53%)	23,636 (79.90%)
Cancelled by the provider	15,458 (5.64%)	2,279 (7.70%)
Appointment cancelled by the patient	11,614 (4.24%)	1,280 (4.33%)
Did not Attend (and not cancelled)	14,053 (5.13%)	2,326 (7.86%)
Attended late and seen	1,159 (0.42%)	56 (0.19%)
Attended late and not seen	122 (0.04%)	5 (0.02%)
Total	170,886	29,582

The study is interested whether not attending the appointment is associated with living further away from the hospital. With the idea that not attending an outpatient appointment is a proxy for a patient's level of health.

3.3.7 Measuring the association between travel times and distance to the GP and health outcomes

The first set of models focus on the association between travel times and distances to the patient's registered GP and baseline health measures (EQ-5D-3L index, EQ-5D VAS, Self-Reported General Health, OHS and OKS). This is considered from the perspective of whether unequal access to the GP is associated with a poorer baseline (pre-operation) health. A number of studies included in Chapter 2 concluded that patients were more likely to have worse health outcomes if they lived further from the GP practice such as Jones et al. (2008b). The models in this section also assess whether this is also true for OA patients who have undergone a THR or TKR.

The first set of models for access to the GP are shown in Table 31. They include a range of different ways of including travel time and distance (both continuous, log transformed and categorical) and are not adjusted for 'other' explanatory variables. The RMSE , R^2 and where applicable pseudo R^2 are provided in the tables.

The results for the unadjusted THR models shows that including travel time as a continuous variable that patients living further from their GP have a higher baseline EQ-5D-index score ($p<0.1$), are more likely to report a higher baseline EQ-5D VAS, report being more likely to be in a better general health category and a higher OHS baseline score. Including travel time as a categorical variable compared to those living < 1 minute from their GP living further from the GP is associated with a higher baseline EQ-5D-3L, EQ-5D VAS score, better General Health Category and higher OHS score. The R^2 values indicate that the models with travel times as a category are a slightly better fit for the data and the RMSE are also lower again indicating a better fit. The results are of the same magnitude for the distance calculations.

The results show that the further a THR patient lives from their registered GP the more likely they will have a higher baseline EQ-5D-3L index, higher EQ-5D VAS score, be more likely in a better general health category and have a higher baseline OKS/ OHS (although not all results are statistically significant). This is not the result that was expected, but shows that there is evidence of an association between the THR living closer to their registered GP and having poorer baseline health prior to undergoing the THR. It should be noted that the results were not all statistically significant.

There is a similar picture for the unadjusted TKR models which show that as travels times to the GP increase patients are more likely to report that their baseline self-reported health measures are better.

The next models adjust for the other potential explanatory variables discussed in Table 15. Identified in the literature. The adjusted models focusing on travel time to the GP (as a categorical variable) are shown in Table 32. This include the explanatory variables of gender, deprivation quintiles, comorbidities, age, living arrangements, ethnic group, days on the waiting list and month completed the questions (winter vs. all other).

Focusing on EQ-5D-3L first – the adjusted model shown in Table 32 indicates that travel time (as a categorical variable) is positively associated with EQ-5D-3L index score for THR patients (but not statistically significant), but shows mixed results for TKR with those travelling in the categories 1 min to 5 mins having an increase in baseline EQ-5D index compared to the

baseline and those travelling > 5 mins a worse baseline EQ-5D-index value (none of these associations are statistically significant). The model also shows that living in a more deprived quintile, having comorbidities (compared to none), living alone and having mobility problems were all associated with a worse (lower) baseline EQ-5D-3L index values. Living alone was associated with a statistically significant lower EQ-5D-3L for those THR patients. Being between 60 and 80 years old (compared to being < 60 years old) was associated with a statistically significant higher baseline EQ-5D-3L index for those with THR and TKR. Indicating that those under the age of 60 had poorer self-assessed baseline EQ-5D-3L than those older than 60 years old for both TKR and THR and poorer self-assessed baseline EQ-5D-3L than for those > 80 years old, but only for TKR operations.

Focusing on the EQ-5D VAS, there were mixed results. There was a positive association (higher baseline EQ-5D VAS) with increasing travel time to the GP for THR and TKR patients, (but neither were statistically significant). Being female, living in the worst deprivation quintile, having comorbidities and living alone were all associated with a lower baseline EQ-5D VAS score for THR and TKR. Non-white British patients had statistically significant lower baseline EQ-5D VAS compared to White British ($p<0.001$) for TKR operations.

The results for Self-Reported General Health showed that living further away from the GP was associated with an increased likelihood of reporting being in a worse general health category for TKR patients (but not THR patients). Having comorbidities, living alone, being white British and increasing days on the waiting list at baseline were associated with a statistically significant increase in the likelihood of being in a worse general health category for both THR and TKR. Non-white British patients were more likely to report being in a better general health category, as was being over the age of 60 compared to being under the age of 60 years old.

For the OHS increasing travel time to the GP was associated with higher baseline OHS compared to the base of < 1 minute, but those travelling > 10 minutes had a negative sign indicating that it was lower (but not statistically significant). For example patients living 10 minutes further away from the GP would have an expected reduction in OHS score of 0.794 compared to the < 1 minutes travel time. Living in a more deprived deprivation quintile, being female, having comorbidities, number of days on the waiting list were all statistically significantly negatively associated with lower OHS baseline score.

For OKS measures patients travelling 1 -3 mins, 3 – 5 mins and 5 – 10 mins were associated with having a higher baseline OKS than those travelling < 1minutes and those travelling > 10 minutes to the GP. For example, for those that lived 10 minutes from the GP would be expected to have a reduction in the OKS score of 0.323. Living in a more deprived area has a statistically significant negative association with the score. For example, a TKR patient living in the worst deprivation quintile would have a lower score by - 4.22 compared to someone in the least deprived quintile (which is above the MCID threshold of 4 for the OKS). Being female was associated with a worse baseline health score. Older patients in the 60 – 80 category had higher baseline scores than those in the < 60 years category and this was statistically significant at $p<0.05$).

One of the key missing pieces of information is how patients have got to the GP given a large number prior to the operation have poor mobility. Only 2% of the sample lived within 250 metres walk of the GP and 17% within half a mile of the GP. The reality of this means that it could be assumed that those living further away would need a vehicle to get to the GP. Possible links with poor accessibility is the worsening of scores, as patients live in more deprived locations. Here there is a link to being less likely to own a vehicle, as car ownership declines as deprivation increases (Norman, 2010). Equally living alone for example, might present problems with getting to the GP if mobility is an issue.

Table 31: Measuring the association between travel time/ distance to the GP and health measures in the unadjusted models

		Health wellbeing measure	EQ-5D-3L Index		EQ-5D VAS		General Health		OHS	OKS
		Model	OLS		OLS		Ordered Logit		OLS	
		Interpretation	+ ve value is better		+ ve value is better		-ve value is an improvement		+ ve value is better	
		Sub group	THR	TKR	THR	TKR	THR	TKR	THR	TKR
		Sample (n)	4,484	5,508	4,317	5,271	3,526	4, 277	4, 554	5,621
Travel Time (mins)	Continuous	Travel Time, (mins)	0.003*	0.001	0.161	0.177**	-0.017	- 0.017*	- 0.0004	0.058*
	R^2/ RMSE		0.0007/0.324	0.0002/0.3158	0.0005/21.912	0.0008/20.673	(0.0003)	(0.0003)	0.0000/8.214	0.0006/7.706
	Categorical	Base = < 1 mins	--	--	--	--	--	--	--	--
		1 – 3 mins	0.032	0.025	2.21	1.554	- 0.135	- 0.099	0.692	0.660
		3 – 5	0.038	0.026	3.106*	1.089	- 0.058	- 0.009	0.708	0.922**
		5 – 10	0.049**	0.022	2.819*	1.835	- 0.261*	- 0.141	0.813	1.022**
		> 10 mins	0.055**	0.043*	3.170	3.363**	- 0.148	- 0.253	0.695	1.179*
	R^2/ (Pseudo R^2)RMSE		0.0013/0.324	0.0006/0.3157	0.001/21.914	0.0009/20.672	(0.0008)	(0.0006)	0.0008/8.213	0.0012/7.705
Travel Distance (miles)	Continuous	Travel Distance (miles)	0.006*	0.003	0.248	0.317*	- 0.033	- 0.030	0.047	0.091
	R^2/ RMSE		0.0007/0.324	0.002/ 0.3158	0.0002/21.914	0.0005/20.67	(0.0002)	(0.0002)	0.0000/8.214	0.0003/7.707
	Categorical	Base = < 0.5 miles	--	--	--	--	--		--	--
		0.5 - 1 miles	0.010	0.023*	0.887	0.455	- 0.016	0.020	0.478	0.872**
		1 – 3 miles	0.039**	0.011	1.334	0.695	0.043	0.063	0.786*	0.807**
		> 3 miles	0.002	0.017	1.880	1.506	- 0.141	- 0.059	0.121	0.673
		> 5 miles	0.060**	0.055*	2.679	2.89	-0.194	- 0.389**	0.978	0.941
	R^2/ RMSE		0.0036/0.324	0.001/0.3157	0.0008/21.916	0.0006/20.675	(0.0004)	0.0005)	0.0014/8.211	0.0018/7.7031

(Legend: *P<0.1, **P<0.05, ***P<0.001)

Table 32: Is categorical travel time to the GP associated with poorer health status (adjusted model)

	Health Measure Model Interpretation Sub group	EQ_5D_3L OLS +vs is better THR	TKR	EQ-VAS OLS +ve is better THR	TKR	General Health Ordered Logit - ve is better THR	TKR	OHS OKS OLS + is better THR	TKR
Sample size (n)		4,221	5,200	4,065	4,987	3,319	4,020	4,294	5,310
Travel time (mins) Base = <1)	1 – 3 mins	0.022	0.018	2.349	0.722	- 0.094	0.037	0.362	0.401
	3 – 5 mins	0.029	0.020	2.829*	0.342	- 0.018	0.167	0.362	0.602
	5 – 10 mins	0.024	- 0.0004	1.850	0.191	- 0.115	0.068	0.176	0.304
	> 10 mins	0.031	- 0.0005	1.896	- 0.035	0.045	0.173	- 0.794	- 0.323
Sex (base = male) Female		- 0.074***	- 0.082***	-3.630***	- 4.418 ***	0.067	0.207**	- 3.195***	- 3.110***
Deprivation Quintiles (base = least deprived)	2	- 0.026	- 0.031**	- 1.629	- 0.313	0.036	0.107	- 0.819**	- 1.105**
	3	- 0.024	- 0.058**	- 0.013	-2.379***	0.306**	0.269**	- 0.638**	- 1.970***
	4	- 0.078***	- 0.094***	-2.541**	-4.122***	0.469***	0.529***	- 2.354***	- 3.042***
	5	- 0.112***	- 0.138***	- 4.016**	- 6.551***	0.798***	0.869***	- 3.331***	- 4.219***
Comorbidities (base = none)	1– 2	- 0.080***	- 0.050***	- 6.235***	- 6.137***	0.878***	0.872***	-2.191***	- 1.608***
	>2	- 0.090***	- 0.097***	- 5.477***	- 8.554***	0.929***	1.197***	-2.252***	- 3.421***
Age groups (base = < 60)	60 -80	0.064***	0.107***	6.341***	7.076***	-0.289**	-0.554***	1.462***	2.573***
	>80	- 0.007	0.094***	5.021***	6.460***	-0.132	-0.534***	- 0.399	1.231**
Living Alone (base = not alone) Alone		- 0.021*	0.011	- 1.811**	- 1.912**	0.275***	0.185**	0.058	0.259
Ethnic Group (base = White British) non WB		0.020	- 0.019	0.458	- 3.643***	-0.146	0.391***	-0.019	- 0.677**
Days on the waiting list		0.0001	0.0001**	- 0.006	- 0.004	0.001**	- 0.001**	0.003	0.004**
Season completed the questions (base = winter)		0.019	0.020**	0.890	- 0.561	- 0.233**	- 0.0093	0.531**	0.458**
Constant		0.4211***	0.465***	64.763***	73.835***	N/A	N/A	22.791***	22.79***
R^2 / (Pseudo R^2)/ RMSE		0.059/0.315	0.07/ 0.305	0.045/21.44	0.08/ 19.79	(0.0361)	(0.0454)	0.086/7.883	0.12/7.263

(Legend *P<0.1, **P<0.05, ***P<0.001)

3.3.8 Measuring the association between travel times and distance to the Hospital and health outcomes

The previous section focused on access to the GP and looked at whether living further from the GP was associated with inequalities in baseline health. It showed that there were mixed results with the OHS and OKS identifying a negative association (but not statistically significant) with travelling >10 minutes further to the GP and baseline (<1 minutes) score. This section now looks at whether living further from the THR or TKR hospital that the patient attended is associated with inequalities in change in health measures following the operation (follow up minus baseline). The following outcomes are considered:

- *Change in EQ-5D-3L*
- *Change in EQ-5D VAS*
- *Change in Self- Reported General Health*
- *Change in OHS*
- *Change in OKS*

3.3.8.1 Unadjusted Model: modelling the association between travel time to hospital and health outcomes

The models are presented in each case firstly not accounting for missing data and then secondly, with imputed values. The THR unadjusted models focusing on travel times to the hospital are presented in Table 34 and Table 35 (with imputed missing data) and for TKR in Table 35 and Table 36 (with imputed missing data). The numbers of patients in each of the categories for travel time for each of each of the models in the unadjusted and adjusted analysis are provided in Table 33 for reference.

Table 33: Number (%) of the sample in each of the travel time categories for each of the models

	Model	< 10 mins	10 – 20 mins	20 – 30 mins	> 30 mins	Total
THR	EQ-5D-3L	1,125 (31%)	1,700 (47%)	636 (17%)	175 (5%)	3,636
	EQ-5D VAS	1,079 (30%)	1,699 (48%)	620 (17%)	169 (5%)	3,567
	General Health	1,131(30%)	1,793 (48%)	660 (17%)	178 (5%)	3,762
	OHS	1,475 (30%)	2,331 (48%)	821 (17%)	228 (5%)	4,855
TKR	EQ-5D-3L	1,346 (30%)	2,073 (47%)	803 (18%)	225 (5%)	4,447
	EQ-5D VAS	1,292 (30%)	2,034 (47%)	774 (17%)	211 (5%)	4,311
	General Health	1,335 (31%)	2,047 (47%)	742 (17%)	231 (5%)	4,355
	OKS	1,851(31%)	2,764(47%)	1,020(17%)	291(5%)	5,926

Focusing on the THR patients first. As shown in Table 34 increasing travel time to the hospital (as a continuous measure) had a positive association with improvements in changes in health for the THR patients. The results for the EQ-5D VAS and OHS showed that as travel times increased the EQ-5D VAS and OHS were higher (better). This result became mixed where travel time was included as a categorical variable Compared to travelling < 10 mins to the hospital, travelling 10 – 20 and 20 – 30 mins had a positive association (improvement), but travelling greater than 30 minutes a negative association, which was statistically significant for the change in OHS and change in EQ-5D-3L score. This implies that those living closer and those living the further away from the hospital have the worst health outcomes following the operation. Focusing on the MCID thresholds the change in OHS in the unadjusted model shows a difference of -1.423 and whist statistically significant at $p<0.1$ is not large enough to pass the MCID thresholds discussed in section 3.2.4.2. The results do however show a similar picture to the U shaped results presented in Kim et al. (2000). Including the imputed missing data gives the same results (Table 35). Therefore indicating that the results hold for the total patient population.

For the TKR population Table 36 shows a statistically significant positive association with changes in health measures when travel time is included as a continuous variable (indicating that as patients travel further to the hospital that they have an improvement in their health outcomes. When travel time is included as a categorical variable travelling 10 – 20 mins and 20 – 30 mins (compared to < 10 minutes) to the hospital is associated with a statistically significant positive association for EQ-5D-3L, EQ-5D VAS and OKS, but travelling > 30 mins is associated with a statistically significant negative association with OKS. None of the results for the unadjusted models were statistically significant for self-reported general health. Imputing the missing data does not change the overall message. It shows that using the continuous variable hides some of the changes that occur for patients living > 30 mins compared to those living < 10 mins from the hospital.

Table 34: Are changes in self-reported health following a THR associated with travel time to hospital? (unadjusted)

	Health Measure Model Interpretation Sub group	EQ-5D-3L OLS +vs is better THR	 THR	EQ-5D VAS OLS +ve is better THR	 THR	General Health Ordered Logit + ve is better THR	 THR	OHS OLS + is better THR	 THR
Baseline Health Measure		-0.744***	-0.746***	- 0.730***	- 0.731***	-1.574	-1.577***	- 0.581***	- 0.585***
Travel time (mins)		0.001		0.087**		-0.007*		0.025	
Travel time (base = < 10 mins)	10 - 20		0.012		1.953**		- 0.171**		0.886**
	20 - 30		0.031**		2.564**		-0.257**		0.995**
	>30		- 0.047*		1.361		0.156		- 1.423*
Constant		0.667***	0.665***	55.872***	55.676***			30.120***	29.908***
R^2 (pseudo R^2)		0.483	0.484	0.445	0.4462	0.1398	0.141	0.218	0.221
RMSE		0.246	0.246	17.539	17.533			8.954	0.946

*(Legend *P<0.1, **P<0.05, ***P<0.001)*

Table 35: Are changes in self-reported health following a THR associated with travel time to hospital? (unadjusted including imputed data)

	Health Measure Model Interpretation Sub group	EQ-5D-3L OLS +vs is better THR	 THR	EQ-5D VAS OLS +ve is better THR	 THR	General Health Ordered Logit + ve is better THR	 THR	OHS OLS + is better THR	 THR
Baseline Health Measure		-0.724***	- 0.726***	-0.730***	-0.732***	-1.543***	-1.546***	-0.574***	-0.574***
Travel time (mins)		0.001		0.087**		- 0.007*		0.031**	
Travel time (base = < 10 mins)	10 - 20		0.015*		2.129**		-0.172**		0.8075**
	20 - 30		0.076***		2.799**		-0.247**		1.081**
	> 30		- 0.077*		1.125		0.092		-0.752*
Constant		0.649***	0.653***	55.872***	55.43***			29.73***	29.584***

Table 36: Are changes in self-reported health following a TKR associated with travel time to hospital? (unadjusted model)

	Health Measure Model Interpretation Sub group	EQ-5D-3L OLS +vs is better TKR	 TKR	EQ-5D VAS OLS +ve is better TKR	 TKR	General Health Ordered Logit + ve is better TKR	 TKR	OKS OLS + is better TKR	 TKR
Sample		4,447		4,311		5,926		4,879	
Baseline Health Measure		- 0.708***	- 0.708***	-0.592***	- 0.591***	-1.681***	-1.681***	- 0.481***	- 0.483***
Travel time (mins)		0.001**		0.126***		– 0.006*		0.062***	
Travel time (base = < 10mins)	10 - 20		0.033**		1.750**		-0.113*		1.26***
	20 - 30		0.035**		2.978***		-0.097		1.69***
	>30		0.016		4.371		-0.258		- 1.74*
Constant		0.571***	0.570***	41.753***	42.829			23.389***	23.42***
R^2 (pseudo R^2)		0.432	0.433	0.3097	0.3102	(0.154)	(0.154)	0.134	0.136
RMSE		0.251	0.250	17.556	17.553			9.377	9.364

(Legend - *P<0.1, **P<0.05, ***P<0.001)

Table 37: Are changes in self-reported health following a TKR associated with travel time to hospital? (unadjusted model) including imputed data

	Health Measure Model Interpretation Sub group	EQ-5D-3L OLS +vs is better TKR	 TKR	EQ-5D VAS OLS +ve is better TKR	 TKR	General Health Ordered Logit + ve is better TKR	 TKR	OKS OLS + is better TKR	 TKR
Baseline Health Measure		- 0.686***	-0.687***	- 0.590***	-0.590***	-1.407***	-1.408***	- 0.456***	- 0.459***
Travel time (mins)		0.002**		0.127***		- 0.013***		0.064***	
Travel time (base = < 10mins)	10 - 20		0.033***		1.690**		-0.185**		1.233***
	20 – 30		0.038***		2.953***		-0.282***		1.693**
	>30		0.024		4.148		- 0.414		- 1.111*
Constant		0.552***	0.565***	41.389***	41.819***			23.149***	23.227

(Legend - *P<0.1, **P<0.05, ***P<0.001)

3.3.8.2 Adjusted Models: modelling the association between travel time to hospital and health outcomes

The THR adjusted models focusing on travel times to the hospital are presented in Table 38 (without imputed data) and Table 39 (with imputed missing data) and for TKR in Table 39 (without imputed data) and Table 40 (with imputed data). The models implement travel time as a continuous variable and categorical variable split into the categories of < 10 mins, 10 – 20 and 20 – 30 minutes and > 30minutes. The adjusted models controlled for gender, deprivation quintiles, comorbidities, age groups (< 60 years old, 60 – 80 and > 80 years old), living arrangements, ethnic group, days in hospital following the operation, hospital provider (NHS vs private provider) and hospital quality (base = needs improving vs Excellent/ good).

Starting with the data for the THR patients including travel time to the hospital attended, as a continuous variable is associated with positive (but non-statistically significant) change in the EQ-5D-3L index score. However when included as a categorical variable there are mixed results compared to travelling < 10 minutes (road network car travel time) there is a positive association for those travelling between 20 and 30 minutes, but a negative association for those travelling > 30 minutes to the hospital compared to 10 minutes. Controlling for the 'other' explanatory variables has not changed the overall signs and significance levels of the results. Those living closest and furthest away are associated with poorer self-reported health outcomes. Being female, living in a more deprived quintile, having comorbidities, and spending more days in hospital following the operation were all associated with a statistically significant negative association with change in EQ-5D-3L index score. Being over the age of 60 (compared to under 60) was associated with the positive association. Including the missing data resulted in the same pattern of results, but only the values for those travelling 20 - 30 minutes (compared to < 10 minutes) were statistically significant, as shown in Table 39. Days in hospital, having comorbidities and living in the most deprived residential quintiles were still statistically significantly negatively associated with change in EQ-5D-3L score.

For the EQ-5D VAS increasing travel time to the hospital was associated with a positive (but non-statistically significant) association with change in EQ-5D VAS score. Again when included as the categorical variable those living 10 – 20 minutes & 20 - 30 minutes (compared to those living < 10 minutes away) had a statistically significant ($p<0.1$) positive association with improvements in the change in EQ-5D VAS and again those living > 30 minutes away had a negative association, but in this case this was not statistically significant. Living in a more deprived area, having comorbidities, being over the age of 80 (compared to < 60 years old)

and greater days in hospital following the operation were all associated with a negative association with change in EQ-5D VAS score. Including the missing data did not change the overall message.

For the self-reported general health measure there were no statistically significant associations with travel time to the hospital. Travelling 20 – 30 minutes compared to < 10 minutes to the hospital was associated with being more likely in a worse general health category after the operation. Having comorbidities, being over the age of 80, and longer days in hospital were all statistically significant negatively associated with being in a worse general health category following the operation. Including the missing data did not change the overall message.

Travel times as a continuous variable shows a negative (but not statistically significant) association with OHS, but as a categorical variable the results were again mixed. Those travelling 20 - 30 minutes away from the hospital showed a positive association (improvement) in change of OHS score compared to those living closer and those living > 30 minutes a negative association (worse) change of OHS score compared to those living < 10 minutes away. The imputed data presented similar pattern to the results, with the coefficient for travelling > 30 minutes to hospital was still negative and statistically significant. The OHS model was the only THR model that showed a statistically significant and positive association with having the operation at a privately operated hospital. This was also statistically significant after imputation ($p<0.05$).

Focusing on the TKR patients. The results of the models are presented in Table 40, after adjusting for gender, age, deprivation, comorbidities, living arrangements, ethnic group, and days in hospital, hospital provider and hospital quality and Table 41 imputing the missing data. For the EQ-5D-3L change in index score there was a positive statistically significant ($p<0.1$) association with increasing travel times, where travel time was included as a continuous variable, so as travel times to the hospital increased the change was higher. This was a small change as a 30 minutes increase in travel time would be associated with a 0.03 increase in EQ-5D-3L. Not large enough to achieve the MCID threshold. The results were mixed for travel time as a categorical variable showed as travel time increased from the base the change in EQ-5D-3L increased. Those who were travelling > 30 minutes (compared to < 10 minutes) showed a positive (but non-statistically significant association). Living alone was shown as a negative (but non-statistically significant) association with change in EQ-5D-3L index. Unlike the THR results hospital quality (attending a hospital that is classed as Excellent/ good compared to need improving) was associated with an improved change in EQ-5D-3L score.

For the EQ-5D VAS results there was a statistically significant ($p<0.05$) positive association between travelling further and change in score for the TKR patients. As can be seen from the categorical travel time this is being driven from those patients who are travelling between 20 – 30 minutes. With those travelling > 30 minutes showing a positive (but non-statistically significant) association. For the TKR, being female, living in a more deprived residential location, having comorbidities and greater number of days in hospital were all negatively associated with change in EQ-5D VAS score. Both attending a private hospital (compared to NHS) and hospital that was classed as Excellent/ good compared to needs improving were both associated with a positive association with change in EQ-5D VAS score, as was being older than 60 years old. Including the data using did not change the overall message.

For the TKR self-reported general health results increasing travel time to the hospital increased the likelihood of being in a worse self-reported general health category, but none of the results were statistically significant. The same results were evident when the missing data was imputed.

For the disease specific OKS measure the results show a positive and statistically significant association at $p<0.1$ with travel time as a continuous variable. This indicates that on average as travel time to the hospital increases by 10 minutes the OKS score will increase by 0.34. This is below the MCID threshold for noting a difference by the patient. When included as a categorical variable the results show that there is a positive statistically significant association between travelling 10 – 20 and 20 – 30 minutes compared to < 10 mins and a higher OKS score, whilst those travelling > 30 minutes have a statistically significant negative association and lower OKS score. A difference in OKS score of -1.692 compared to those travelling < 10 minutes is below the reported MCID thresholds previously discussed (lowest < 3) , but does indicate a potential change in the results for those travelling the furthest. As with the EQ-5D-3L and EQ-5D VAS results hospital quality was a statistically significant predictor of change in OKS score and as for EQ-5D VAS attending a private vs a NHS hospital was positively associated with a positive change in OKS score. The model that imputed data showed the same overall message for travel time for the TKR patients using OKS.

*Table 38: Are changes in self-reported health state following an THR associated with travel time to hospital? (Legend: *P<0.1, **P<0.05, ***P<0.001)*

	Health Measure Model Interpretation	EQ-5D-3L OLS +vs is better		EQ-5D VAS OLS +ve is better		General Health Ordered Logit -+ ve is better		OHS OLS + is better	
Sample size		3,636		3,567		3,762		3,822	
Baseline Health Measure		- 0.780***	-0.781***	-0.762***	- 0.763***	-1.771***	-1.770***	- 0.622***	- 0.629***
Travel time (mins)		0.0001		0.049		-0.003		- 0.005	
Travel time (base = < 10 mins)	10 - 20		0.003		1.315*		- 0.118		0.428
	20 - 30		0.015		1.567*		- 0.158*		0.301
	>30		- 0.047		- 0.304		0.239		- 1.593*
Sex (base = male)	Female	- 0.015*	- 0.015*	- 0.382	- 0.346	0.116*	0.111	- 0.263	- 0.244
Deprivation Quintiles (base = least deprived)	2	0.014	0.015	- 0.360	-0.306	- 0.083	-0.094	0.322	0.355
	3	- 0.004	- 0.002	- 0.302	- 0.232	- 0.012	-0.029	- 0.653*	- 0.623*
	4	- 0.041**	- 0.038**	-2.394***	-2.384**	0.283**	0.262**	- 1.729**	-1.680***
	5	- 0.060***	-0.058***	-3.778***	- 3.602***	0.252**	0.221**	- 3.071***	-2.998***
Comorbidities (base = none)	1– 2	- 0.062***	- 0.061***	- 6.062***	- 6.047***	0.781***	0.781***	- 1.657***	-1.659***
	>2	- 0.088***	- 0.088***	- 8.966***	- 8.974***	1.147***	1.151***	- 2.581***	-2.589***
Age groups (base = < 60)	60 - 80	0.040***	0.040***	0.297	0.242	-0.009	-0.002	0.805*	0.769**
	>80	0.037**	0.036**	- 2.26*	- 2.317*	0.093	0.099	- 0.817	-0.866
Living Alone (base = not alone)		0.007	0.007	0.563	0.549	0.091	0.092	- 0.201	- 0.213
Ethnic Group (base = White British)		- 0.002	-0.001	0.289	0.432	0.067	0.052	0.006	0.385
Days in hospital following operation		-0.007***	-0.007***	- 0.478***	-0.477***	0.034***	0.034***	- 0.328***	- 0.324***
Hospital provider (base = NHS)	Private	- 0.001	0.0001	-0.466	- 0.554	0.038	0.044	0.971**	0.906**
Hospital Quality (base = Needs Improving) Excellent/ good		0.008	0.009	0.467	0.597	-0.010	-0.022	- 0.059	0.017
Constant		0.749***	0.746***	65.149***	64.887***			33.877***	33.679***
R^2 / RMSE (0.1621)		0.508/0.240	0.509/ 0.240	0.478/ 17.05	0.479/17.048	(0.1617)	(0.1621)	0.267/ 8.683	0.267/8.681

Table 39: Are changes in self-reported health following a THR associated with travel time to hospital (imputing for missing data)?

	Health Measure	EQ-5D-3L		EQ-5D VAS		General Health		OHS	
	Model Interpretation Sub group	OLS +vs is better THR	THR	OLS +ve is better THR	THR	Ordered Logit + ve is better THR	THR	OLS + is better THR	THR
Baseline Health Measure		- 0.763***	-0.764***	- 0.762***	- 0.763***	-1.739***	-1.740***	- 0.649***	- 0.650***
Travel time (mins)		0.0002		0.043		-0.002		0.010	
Travel time (base = < 10mins)	10-20 – 30		0.002		1.399**		-0.104		0.392
	20 - 30		0.058**		1.658***		-0.135		0.321*
	>30		- 0.063		- 0.413		0.191		- 0.852*
Sex (base = male) Female		- 0.009	-0.008	- 0.329	- 0.319	0.118*	0.116*	- 0.313	- 0.301
Deprivation Quintiles (base = least deprived)	2	0.015	0.015	-0.498	- 0.447	-0.084	-0.094	0.336	0.361
	3	-0.009	-0.008	-0.588	- 0.523	-0.003	-0.018	- 0.635	- 0.607
	4	-0.037**	-0.035**	-2.360**	- 2.34**	0.277**	0.259**	- 1.638**	- 1.604***
	5	-0.061***	-0.060***	- 3.704***	- 3.539**	0.267**	0.241**	- 3.008***	- 2.956**
Comorbidities (base = none)	1– 2	- 0.063***	-0.063***	- 6.047***	- 5.846***	0.781***	0.780***	-1.795***	-1.787***
	>2	- 0.086***	- 0.086***	- 9.201***	-9.333***	1.140***	1.141***	-2.413***	- 2.404***
Age groups (base = < 60)	60 - 80	0.044***	0.0438***	0.286	0.145	-0.006	-0.003	0.774***	0.756**
	>80	0.040**	0.040**	- 2.125*	- 2.486*	0.084	0.088	- 0.714	- 0.741
Living Alone (base = not alone)		0.004	0.004	0.580	0.505	0.090	0.092	- 0.199	- 0.214
Ethnic Group (base = White British)		-0.007	- 0.006	0.447	0.402	0.064	0.053	0.034	0.075
Days in hospital following operation		-0.007***	- 0.006***	-0.499***	- 0.488***	0.033***	0.033***	- 0.313***	- 0.3010***
Hospital provider (base = NHS) Private		0.002	0.004	- 0.527	- 0.477	0.029	0.0344	0.986**	1.001**
Hospital Quality (base = Needs Improving) Excellent/ good		0.006	0.005	0.507	0.584	-0.016	-0.027	0.021	0.090
Constant		0.721***	0.719***	65.327***	64.873***			33.641***	33.510***

(Legend: *P<0.1, **P<0.05, ***P<0.001)

*Table 40: Are changes in self-reported health following a TKR associated with travel time to hospital? - (Legend *P<0.1, **P<0.05, ***P<0.001)*

	Health Measure	EQ_5D_3L (OLS)		EQ-VAS (OLS)		General Health		OKS	
	Model Interpretation	OLS +vs is better		OLS +ve is better		Ordered Logit + ve is better		OLS + is better	
Sample (n)		3,636		3,567		3,449		4,045	
Baseline Health Measure		- 0.752***	-0.752***	-0.645***	- 0.644***	-1.79***	-1.79***	- 0.559***	- 0.561***
Travel time (mins)		0.001*		0.073**		- 0.003		0.034*	
Travel time (base = < 10mins)	10 – 20		0.018**		0.81		- 0.076		0.677**
	20 - 30		0.014		1.65**		- 0.037		0.960**
	>30		0.022		3.260		- 0.162		-1.692*
Sex (base = male)		0.001	0.001	- 1.137**	- 1.123**	0.184***	0.184***	0.258	0.250
Deprivation Quintiles (base = least deprived)	2	- 0.009	- 0.010	-0.625	- 0.613	0.048	0.054	- 0.453	- 0.446
	3	-0.009	-0.010	-1.374	-1.328	- 0.019	-0.011	- 0.981**	-0.962**
	4	- 0.046***	- 0.047***	-3.119***	-3.084***	0.151*	0.161*	-1.953***	-1.921***
	5	- 0.057***	- 0.057***	-3.242***	-3.171***	0.171**	0.177**	-2.538***	-2.486***
Comorbidities (base = none)	1-2	- 0.035***	- 0.035***	-3.852***	-3.836***	0.543***	0.543***	-1.100***	- 1.104***
	>2	- 0.023	- 0.023	-7.386***	- 7.386***	0.0.459***	0.458	-2.110***	- 2.126***
Age groups (base = < 60)	60 – 80	0.088***	0.088***	4.054***	4.042***	0.186	0.088	2.855***	2.805***
	>80	0.103***	0.103***	3.292**	3.268**	- 0.347*	0.190*	2.942**	2.942**
Living Alone (base = not alone)		- 0.006	- 0.006	- 0.342	- 0.337	0.069	0.069	- 0.325	0.316
Ethnic Group (base = White British)		- 0.016	- 0.015	-1.240	- 1.290	-0.169	-0.171**	-1.196**	-1.169**
Days in hospital following operation		- 0.011***	- 0.011***	-0.451***	- 0.449***	0.011	0.011	- 0.399***	- 0.388***
Hospital provider (base = NHS) Private		0.012	0.010	2.371**	2.35**	-0.108	-0.095	1.251**	1.211**
Hospital Quality (base = Needs Improving) Excellent/ good		0.028**	0.030***	1.536**	1.558**	-0.073	-0.083	0.455	0.566*
Constant R^2 / RMSE /(Pseudo R^2)		0.600*** 0.464/ 0.244	0.602*** 0.466/ 0.243	47.340*** 0.344/ 17.14	47.558*** 0.344/ 17.14	(0.1633)	(0.1633)	24.817*** 0.183/9.117	24.821*** 0.184/9.113

Table 41: Are changes in self- reported health a TKR associated with travel time to hospital (imputing for missing data)? (*P<0.1, **P<0.05, ***P<0.001)

	Health Measure	EQ_5D_3L		EQ-VAS		General Health		OKS	
	Model Interpretation	OLS +vs is better		OLS +ve is better		Ordered Logit + ve is better		OLS + is better	
Baseline Health Measure		- 0.734***	- 0.734***	-0.643***	- 0.646***	- 1.620***	- 1.62***	-0.544***	- 0.544***
Travel time (mins)		0.001		0.066*		-0.006*		0.035**	
Travel time (base = < 10mins)	10 - 20		0.017**		0.693		-0.0698		0.613**
	20 - 30		0.015		1.616**		- 0.100		0.878***
	>30		0.012		2.938		-0.293		- 1.294*
Sex (base = male)	Female	0.002	0.002	- 1.094*	- 1.08*	0.139**	0.139**	0.335	0.339
Deprivation Quintiles (base = least deprived)	2	- 0.009	- 0.010	-0.673	- 0.629	0.124	0.129	- 0.416	- 0.431
	3	-0.011	- 0.011	-1.531*	- 1.3560*	0.029	0.034	- 0.859*	- 0.853*
	4	-0.042**	- 0.042***	-3.149**	- 3.070**	0.279**	0.286**	- 2.032***	- 2.024***
	5	- 0.061***	- 0.061***	-3.513***	- 3.294***	0.479***	0.486***	- 2.630***	- 2.601***
Comorbidities (base = none)	1– 2	- 0.035***	- 0.035***	- 3.821***	- 3.728***	0.637***	0.637***	-1.130**	- 1.121***
	>2	-0.045**	- 0.045**	-7.254***	-7.392***	0.849***	0.849***	-2.172**	- 2.178**
Age groups (base = < 60)	60 - 80	0.090***	0.090***	4.158***	4.101***	- 0.175**	- 0.174**	2.801***	2.758***
	>80	0.098***	0.097***	3.403**	3.292**	-0.072	- 0.068	2.804***	2.722***
Living Alone (base = not alone)		-0.011	- 0.011	-0.293	- 0.493	0.084	0.083	0.261	0.252
Ethnic Group (base = White British)		-0.029**	- 0.027**	-1.213	- 1.195	0.122	0.120	- 1.340***	-1.322***
Days in hospital following operation		-0.009***	- 0.008***	-0.433***	-0.439***	0.045***	0.045***	- 0.383***	- 0.383***
Hospital provider (base = NHS) Private		0.019	0.017	2.383**	2.424**	-0.021	- 0.012	1.272**	1.204**
Hospital Quality (base = Needs Improving) Excellent/ good		0.032***	0.032***	1.530**	1.534**	-0.115*	- 0.123*	0.467	0.572*
Constant		0.570***	0.566***	47.148***	47.484***			24.720***	24.831***

3.3.8.3 Access to the Hospital: Length of Stay

What the study wanted to know is whether living further from the hospital in which the patients were treated was associated with spending a longer time in the hospital (in days) from admission to discharge, as a proxy measure for health outcomes.

The results of the statistical models are shown in Table 42. In the unadjusted model including travel times as a continuous variable, travel time in minutes is associated with a positive (but a statistically insignificant) association with LoS in hospital for the THR patients and a negative (but a statistically insignificant) association with LoS in hospital for the TKR patients. Including travel time as a categorical variable shows mixed results. For the THR model travelling 10-20 and 20 – 30 minutes in the unadjusted model is associated with a shorter stay than those travelling < 10 minutes , for those travelling > 30 minutes is associated with a longer stay in hospital ($p<0.05$). For the TKR model travelling 10 – 20 minutes compared to < 10 minutes is associated with a reduction in average LoS of 0.416 ($p< 0.05$), but those travelling > 30 minutes an increase in length of stay of over 1 day ($p<0.05$). In both cases (THR and TKR) travelling > 30 minutes to the hospital compared to < 10 minutes is associated with a stay in longer stay in hospital.

The adjusted models controlling for gender, age, deprivation, comorbidities, living arrangements, ethnic groups, days on the waiting list season of the operation, type of hospital attended and hospital quality are also presented in Table 42. For THR patients the adjusted model with travel time as a continuous variable shows a statistically significant positive association with LoS for THR patients for every extra minute travelled the LoS increases by 0.0172 days. For the adjusted model with travel time as a categorical variable those travelling > 30 minutes compared to < 10 minutes to the hospital is associated with an increased stay in hospital of 1.897 days ($p<0.05$). Other explanatory variables that had a statistically significant association with LoS for THR patients were being female, living in a more deprived residential quintile, having comorbidities, being older and living alone. Variables associated with reducing the length of stay were attending a hospital that was classed as Excellent or Good (compared to need improving) attending a privately provided hospital, having an appointment in winter, number of days on the waiting list, and being from a Non-White British ethnic group.

The results show that those THR patients travelling > 30 minutes are spending on average 1.897 days longer in hospital than those who travelled < 10 minutes. Those TKR patients who travelled greater than 30 minutes spent on average 1.884 days longer in hospital than those who travelled

< 10 minutes. The other predicting variables associated with staying longer in hospital include having comorbidities, living alone, being older than 60 and being in a higher residential deprivation quintile.

3.3.8.4 Access to the Hospital: Missing Appointments

As discussed earlier there are some implications both for the NHS and the patient of missed appointments in terms of patients delayed attendance at hospital. The statistical models that were run to assess whether living further from the hospital is associated with a higher likelihood of missing an appointment are shown in Table 43. In the logit model if the patient attended the appointment or the appointment was cancelled by the provider (hospital) this is a 0 and if the appointment was cancelled by the patient, or the patient did not attend and did not cancel or attended late and was not seen this is represented by 1. A negative coefficient is interpreted as being more likely to attend.

The results are split into the OA model and RA model.

For the OA model the results indicate that those patients living 20 – 30 and > 30 mins away from the hospital compared to < 10 minutes are more likely to attend the outpatient hospital appointment. They are less likely to miss an appointment if they are 60 – 80 years old (compared to under 60) or are White British or male. This is perhaps counter intuitive to the literature, which suggests that having to travel further to get to the hospital would be associated with being more likely to miss an appointment. The results show that living in a more deprived residential location is associated with being more likely to miss an appointment. Living in a rural as opposed to urban area was associated with a higher likelihood of missing an appointment. Critically this analysis shows that rather than those patients living further away from their outpatient appointment not attending it is those that live closest (using road network travel times) that have a higher likelihood of not attending the appointment For the RA model again those who live the furthest away > 30 minutes compared to < 10 minutes are more likely to not miss their appointment, with similar associations for the other explanatory variables included in the models.

*Table 42: Is travel time associated with length of stay in hospital? Model OLS (Legend *P<0.1, **P<0.05, ***P<0.001)*

		Sample THR	THR +ve = Longer stay				Sample TKR	TKR + ve = Longer stay			
	Sub group	No.	unadjusted	Adjusted	Unadjusted	Adjusted	No.	Unadjusted	Adjusted	Unadjusted	Adjusted
Travel time (mins)		4,855	0.003	0.0172**			5.929	-0.003	0.008		
Travel time categories	Base < 10mins	1,475					1,851				
	10 – 20	2,331			- 0.094	0.025	2,764			-0.416**	-0.303**
	20 – 30	821			- 0.119	0.139	1,020			- 0.227	-0.123
	> 30	228			0.934**	1.897***	291			1.121**	1.884**
Gender (base = male) Female		2,892		0.367**		0.366**	3,186		- 0.107		-0.114
Deprivation Quintiles Base = least deprived	2	893		0.202		0.174	1021		0.458**		0.444**
	3	1005		0.821***		0.787***	1164		0.090		0.068
	4	1045		0.312*		0.264	1340		0.101		0.065
	5 (most deprived	986		0.444**		0.383**	1470		0.278		0.216
Comorbidities (base = none)	1– 2	1,388		0.709***		0.703***	2016		0.887***		0.874***
	>2	285		1.598***		1.600***	387		1.887***		1.871***
Age groups (base = < 60)	60 - 80	3,316		1.043***		1.064***	4,377		0.429**		0.452**
	>80	501		3.030***		3.049***	591		2.675***		2.711***
Living Alone (base = not alone) Alone		1,402		1.042***		1.050***	1,515		1.013***		1.018***
Ethnic Group (base = White British) non White British		543		-0.501**		- 0.517**	844		-0.303 *		- 0.332**
Days on the waiting list		4,855		- 0.001		-0.001	5,929		-0.002**		-0.002**
Season had operation (base =not winter) Winter		4,855		- 0.306**		- 0.301***	5,929		- 0.298**		- 0.292**
Hospital Provider Type (Base = NHS) Private Hospital		827		- 0.9829***		- 0.820***	860		- 1.333***		- 1.313***
Hospital Quality (Base =Needs Improving) Excellent/ Good		2,120		- 0.929***		- 0.958***	2334		-0.778***		-0.815***
Constant		--	5.266***	4.419***	5.365***	4.642***	--	5.528***	6.533***	5.720***	6.811***
R^2		--	0.0000	0.121	0.001	0.123	--	0.000	0.092	0.003	0.085
RMSE			4.146	3.925	4.145	3.922		4.421	4.282	4.416	4.276

Table 43: Is travel time to hospital associated with not attending outpatient appointments for OA and RA patients?

	Interpretation	Number Attended	Number Missed	-ve means more likely to attend		No. Attended	No. Missed	-ve means more likely to attend	
	Model	OA Patient Logit Model				RA Patient Logit Model			
Travel time (mins)		163,543	14,813	- 0.007		19,490	2,458	- 0.006*	
Travel time categories	< 10 minutes	72,738	6,796		--	10,676	1,345		--
	10 - 20	69,239	6,329		0.023	7,011	889		- 0.003
	20 - 30	16,475	1,344		- 0.161***	1,571	211		0.045
	>30	5,054	343		- 0.417***	232	13		- 0.859**
Gender (base = male) Female		98,226	9,154	0.034*	0.035*	14,684	1,908	0.179**	0.179**
Deprivation Quintiles 1 = least deprived	1	16,324	865	--	--	1,361	140	--	----
	2	30,316	2,258	0.293***	0.293***	3,620	438	0.476***	0.477***
	3	29,792	2,435	0.385***	0.384***	3,662	472	0.536***	0.544***
	4	38,415	3,861	0.591***	0.596***	5,497	707	0.544***	0.555***
	5 (most deprived	48,696	5,394	0.669***	0.680***	5350	737	0.619***	0.631***
Comorbidities	0	81,277	5,549	---	--	--	--	--	---
	1– 2	57,322	5,633	0.315***	0.315***	14,582	1,644	--	---
	>2	24,944	3,631	0.632***	0.634***	4,908	814	0.392***	0.395***
Age groups (base = < 60)	60 - 80	91,037	6,408	- 0.354***	- 0.357***	11,054	1,472	0.139**	0.139**
	>80	30,071	4,473	0.269***	0.267***	2,541	349	0.089	0.090
Ethnic Group (base = Other) White British		123,156	10,702	- 0.236***	- 0.233***	15,799	1,833	- 0.416***	- 0.407***
Rural Urban (Base = urban) Rural		6,325	788	0.529***	0.518***	890	108	- 0.013	- 0.028
Month (Base = non winter) Winter		38,819	3,812	0.109***	0.109***	4,315	602	0.0603	0.061
Constant				-2.963***	-3.047			-2.796	-2.878***
Pseudo R^2				0.028	0.0281			0.0125	0.0130

3.4 Discussion

This chapter has sought to use THR and TKR patient data collected by the HES-PROMS linked dataset to gain a greater understanding of the potential link between travel time to hospital and the GP and health. It has focused on the HES-PROMS dataset, as the basis for this analysis, as this linked dataset included variables that could be used to calculate the travel times and distances to the healthcare facilities and includes data collected about the patients' health. Some key observations that have emerged from the results are discussed next.

3.4.1 Using PROMS health measures

The study used a variety of measures of heath and proxy measures available within the HES-PROMS dataset including self-reported; EQ-5D-3L domains, EQ-5D VAS, OHS, OKS and General Health and those derived from hospital records, LoS and Missed outpatient appointments. This chapter sought to determine whether it was possible to use the health and wellbeing measures (EQ-5D-3L, EQ-5D VAS, Self-Assessed General Health OHS and OKS, LoS and missed appointments) as an health outcome measure to explore the associations with travel time and distance to hospital and the GP. Assessing whether using travel time is associated with changes in self-reported health following a TKR or THR has not previously been published. The systematic review discussed in Chapter 2 found that it was more common to focus on the association between travel time to healthcare and survival or mortality (Zorzi et al., 2012; Tonelli et al., 2007a), or loss to follow up (Giuliani et al., 2016; Kerschbaumer et al., 2012) as the health outcome (or proxy measure). These measures would be less relevant for operations such as a THR, as the majority of patients survive and there is minimal follow up for those patients that do not suffer complications, which can include infections and revisions. The results show that it is possible to explore the association between travel time and distance to health and health outcomes using the five health outcomes measures from the PROMS dataset.

Only the OKS and General Health models showed statistically significant results for the association with travel times to the GP. The disease specific measures were more sensitive to changes in travel times and distances. In terms of measuring the change in health as a result of the TKR operation a pattern emerged of improvements in health for those travelling between 10 and 30 minutes from the hospital and negative association with those travelling > 30 minutes from the hospital. The OKS was most sensitive again to these results with all categories being statistically significant. Only the EQ-5D VAS showed a statistically significant result for the 20 –

30 minutes category. In comparison to the THR operation the same pattern emerged with an improvement in the 20- 30 minutes category and all measures showing a negative association for those travelling > 30 minutes Statistically significant results were gained for the EQ-5D-3L, EQ-5D VAS (at the 20 – 30 minute category) and OHS. Again the most sensitive was the disease specific measures, but interesting that the EQ-5D-3L and EQ-5D VAS were able to identify the same association (though not always at a significance level above 90%). The study found, as was noted by Benson et al. (2016), that the OHS and OKS measures for assessing the changes in score for the THR and TKR operations were the most sensitive, followed by the EQ-5D-3L Index. The results found. as shown in previous studies that patients who have had a TKR had lower gains in health than those who have a THR (Beard et al., 2015).

The missed appointment model revealed that it was those patients that lived the closest (had the shortest travel times) that were more likely miss their outpatient appointments. This result goes against the distance decay concept in the literature, whereby there is a reduction in attendance as patients live further away(Hunter and Shannon, 1985). More work is needed to explore whether this could still be due to a transport and travelling issue. Those that travelled the furthest were statistically significantly more likely to spend more days in hospital, as were patients who lived alone, those who were older and those with greater comorbidities. Those spending longer on the waiting list for their THR or TKR were more likely to spend less time in hospital following the operation, this could be due to those with more urgent cases (with complications) being seen quicker. This may change in the future, as the UK Government had an 18 week waiting target for patients to be referred and have their THR or TKR, limiting the number of patients waiting beyond this timeframe. Due to constraints in the healthcare system this has just recently been relaxed and there is now a three month minimum waiting time and no maximum target reducing the need to keep waiting times below 18 weeks (Donnelly, 2018).

3.4.2 Continuous, Categorical or both

It was anticipated at the start of the study that those patients living further away from the healthcare facilities (GP or hospital) would have worse health outcomes. Findings from the systematic review in Chapter 2 showed the importance of considering travel times and distances as both categorical variables and continuous variables, as the results might differ. This was certainly found to be the case for this patient population. The results showed that using a continuous measure of travel time hid a more mixed result that using the categorical travel time. These models identified a positive (but non-statistically significant) association with change in EQ-5D-3L when travel time was included as a continuous variable, but when included as 4 categories (< 10 minutes, 10 – 20 minutes , 20 – 30 minutes and > 30 minutes) there was a

positive association at 10 – 20 minutes and 20 – 30 minutes (compared to < 10 minutes and a negative association at > 30 minutes (compared to < 10 minutes) indicating a worsening effect. These mixed results would have been missed if the continuous variable alone had been used. As shown in Table 38 including travel time as a continuous variable was associated with a negative (non-statistically significant) association with the OHS score, but when included as a categorical variable there was a positive association (increase in score) for those patients living 20 – 30 minutes away from the hospital attended, but statistically significant negative association for those living > 30 minutes away. Whilst the results were found to be statistically significant the change in scores from travelling further to the hospital > 30 minutes compared to < 10 minutes were not large enough to meet the MCID thresholds currently published in the literature (Beard et al., 2015)of 5 points for OHS and 4 points for OKS.

As noted by Benson et al. (2016) the OKS and OHS are seen as the gold standard measure for identifying differences in the TKR and THR patients and were found to be more sensitive to changes in health outcomes in this study for the models that focused on travel times to hospital. Note that the results did not show any statistically significant associations between travelling further to the GP and health outcomes.

The strongest association is observed with the models focusing on LoS at hospital. With patients on average staying around 2 days longer at hospital if they travelled further than 30 minutes to the hospital to have their operation than travelling < 10 minutes. The same U shaped association is identified with again those patients living in the middle ground 10 – 20 minutes away and 20 – 30 minutes away having a reduction in their LoS compared to those closer and further away. An unexpected result was found with those travelling further being more likely to attend their outpatient appointments than those living closer to the hospital. Again a potential impact from those patients living closest to the hospital in terms of travel times, but maybe not in terms of ease of access as discussed in Chapter 1. The other factors that influence ease of access are considered in more detail in the next Chapter.

The picture is of a U shaped curve, whereby those living closest and furthest away have the worst self-assessed health following the THR or TKR operation and those in the middle having higher self-assessed health. This distribution was also found in the study by Kim et al. (2000), (although in the disease area of cancer) who found that those who travelled greater than 30km or less than 20km had worse survival than those in the 20 – 30km band.

In this study possible reasons for these differences include that patients are split between travelling further for their THR or TKR or having to attend the hospitals closest to their homes when they are identified as being likely to have potential complications from having the

operation. Feedback from one of the local GPs – suggested that they would always suggest to patients that they should attend the 'local' / 'nearest' hospital if they thought that the patient would have any issues whether those of getting there or potential complications following the operation due to their health. This could be one potential explanation of why those living the closest have worse outcomes and stay in hospital longer than those just 10 minutes further away. In this study we controlled for baseline differences in health and the number of comorbidities a patient has (the study included the categories of 0, 1-2,> 2 comorbidities). The Charlson Index, used to calculate the number of comorbidities from the patient's hospital records goes up to 12, so it could be that some patients with the worst levels of health and a large number of comorbidities are hidden by being included in the > 2 comorbidities category resulting in potentially residual confounding. As discussed in the thesis a recent policy change is that CCGs are restricting patients with a BMI > 35 and smokers from having easy access to a THR or TKR. Not controlling for this in the model (as these two variables were not available in the HES-PROMS dataset) may have impacted on the results, as BMI and or smoking might be unmeasured confounders, as they may also have an impact on the patients transport accessibility.

Another potential explanations for the differences in results by travel time to the hospital is incomplete control in the models for patient deprivation, as the deprivations scores are both based on the area that the patient lives in (not patient specific deprivation) and the scores have been banded into quintiles, so reducing the granularity of the data, which could have led to residual confounding and biased the results (Becher, 1992). Another possibility is that as the results of the models are a combination of patients travelling to 31 different hospitals rather than one hospital this may have affected the results. Multi-level modelling early in the model development showed that the hospitals were not all homogeneous in the association between travel time and health outcomes and the results may be due to a high degree of heterogeneity going beyond the type of hospital and hospital quality that was included in the models to control for type of hospital attended.

These differences in results for those living further away from the healthcare facilities has implications for the policy of reconfiguring healthcare facilities, as this policy it has the potential to increase the travel times that some patients have to travel to get to the healthcare facilities. This research indicates that patients that have to travel > 30 minutes to get to the healthcare facilities for their operation, would be associated with worse health outcomes. However, it does also indicate that focusing on travel time alone is not enough, as those living < 10 minutes from the healthcare facility had worse outcomes than those travelling between 10 and 30 minutes.

3.4.3 Would the patients notice the difference in health?

The methodology section discussed that one method that can be used to go beyond assessing whether there is a statistically significant association in the results would be to focus on the MCID. The results for the OKS models indicate that the average difference for patients travelling > 30 minutes to the hospital for a TKR compared to < 10 minutes would be a reduction in OKS of -1.692 and for OHS it is – 1.593 This would not be classed as meeting the threshold by which it would be a noticeable clinical difference for patients, with 4 points for OKS and 5 points difference for the OHS (Beard et al. (2015). What should be noted though is that in using the anchor method that patients in the study by Beard et al, (2015) who rated themselves as " a little worse" on the anchor scale still had on average a 2 point improvement in OHS/ OKS score and those that rated themselves as "much worse" on the anchor scale only showed a small deterioration on the OHS/OKS score of -3.58 compared to the positive side of the scale. Thus implying that the threshold for having a worse health outcome was not symmetrical (and smaller) to an improvement and therefore that actually the threshold by which a patient might notice the difference when it is worse to be smaller. The decline of -1.692/ -1.593 for those travelling over 30 minutes compared to < 10 minutes could therefore be within an acceptable threshold whereby patients would potentially notice a clinical difference due to the decline. This also fits with the loss aversion theory within the behavioural economics literature, which is that people feel their loses much more than their gains derived from Kahneman and Tversky (1979)"Losses loom larger than gains" (p279). A clinically meaningful loss might therefore need an alternative approach for research presented in this study that is showing a reduction rather than an improvement. Further research is needed to explore this area further.

3.4.4 Measuring a patient's transport accessibility to healthcare

One of the key limitations of the HES-PROMS dataset for undertaking these type of analyses focusing on travel times and distances to the healthcare facilities (as a proxy measure for transport accessibility to healthcare) is that data is not currently collected on how patients travelled (e.g. car, bus, PTS, walk) to their appointments. For example is the transport accessibility the same for the following patients who live 20 minutes by car away from the hospital:

- *Patient A who has someone to drive them to the hospital and drop them off at the hospital entrance for their appointment.*
- *Patient B who has had to walk to the bus stop travel by bus and then walk from the bus stop nearest the hospital to the hospital for their appointment.*

The answer is no, but it is not possible to gauge this information from the data available in the HES-PROMS dataset. What is known, is that a significant proportion of patients, 37% of THR and 30% of TKR patients stated that they either could not walk or were limited to walking around the house prior to having the operation thus significantly limiting their transport accessibility.

The study calculated the travel times by car and by bus to assess whether there were any statistically significant differences in travel times. For this WY patient population travel times by bus and walk (if everyone had travelled by bus) would have taken on average 44.13 minutes, with 91 patients not able to make a 10 am appointment had they left their house at 7am and one patient having to travel 2 hours 50 mins on the bus to get there. Compared to an average of 14.85 minutes for travel by car this shows inequalities based on how patients can travel. Further work is needed in the future to be able to identify who those patients might be whose journeys could potentially negatively impact on their health outcomes and create inequalities between different groups based on transport accessibility.

When showing the results of the models to the studies PPI group a discussion was had regarding the fact that whilst living further away made it more difficult, but what really bothered them was the level of comfort whilst travelling, issues included getting into the vehicle, cramped conditions when using the PTS and not knowing how long it would take for the PTS to take them home. All of the members of the group had used the PTS for at least some of their hospital appointments.

3.4.5 Reconfiguring THR and TKR operations

Following on from the 2009 Health Care Act (Department of Health, 2009) patients in the timeframe of this patient population 2009/10 to 2011/12 had, in theory, free choice over where they had their THR or TKR operation. Patients did not all select the closest hospital for their operation with only 36.33% attending the nearest hospital (based on fastest travel time). This is a similar level to that found by Tracey et al., (2005a). Average travel time to the nearest hospital was 9.75 minutes (9.66 – 9.83 CI 95%) compared to 14.85 minutes (14.69 – 15.02 CI 95%) for the actual hospital attended. Reducing choice through reconfiguring where operations take place will have more of an impact on those that might move into the > 30 minute category based on the results of this study. Additionally those who attended their nearest hospital were more likely to be in the most deprived deprivation quintiles ($P<0.001$), where 44% attended their nearest hospital compared to 32% of those in the least deprived quintiles, and have comorbidities whereby 69.7% of those patients with > 2 comorbidities attended their nearest

hospital compared to 35.8% of those with no comorbidities. The policy may have more of a negative association with health outcomes if these individuals have to travel further.

3.4.6 Using patient confidential data

A significant amount of time was allocated in the study to apply for and get ethical approval for accessing the patient level data used in this chapter. One of the key drivers for requesting the patient data was to ensure that the travel times and distances calculated were the most accurate for the study. The alternative was the LSOA, which was also used in this study, as a comparator- requesting this data would have still required ethical approval, but not Section 251 approval. The study compared using the LSOA (which is representative of an average of 672 household) and a full home postcode which has up to 80 households. When using straight-line distance as the calculation method there was no statistically significant difference between using the LSOA and the home postcode. When using the travel distance and the travel time calculations there was a small difference between using the LSOA and the home postcode calculations. It should be noted that for shorter distances (to the nearest hospital) there was a statistically significant difference of 0.25 of a mile, but this difference was reduced as the distances increased. On this basis the results would not have been statistically significantly different if the LSOA calculations had been used instead of the home postcode calculations.

The aspect of the patient data that did have an impact was not knowing the hospital that the patient attended compared to using the nearest and assuming that all patients attended the nearest hospital or GP. This suggests that when accessing data it is this aspect that would be worth investing resources in to access. A comparison between when it is suitable to use the nearest vs using the actual hospital attended is included in the discussions in Chapter 4.

3.4.7 Strengths and Limitations

The key strengths of the research presented in this chapter is that it used a large WY patient secondary dataset (> 10,000 patients) that was linked with patient reported outcomes to explore the association between travel times to hospital and the GP and health (proxy health) outcomes. One of the key weaknesses was that whilst it was possible to calculate the travel times to the healthcare facilities, the study did not have any access to how the patients had travelled. In using the HES-PROMS dataset (due to its completeness in terms of patients' data) it did allow for some of the other potential explanatory factors that affect health outcomes identified in Chapter 1 to be included (e.g. comorbidities. deprivation quintiles, gender , age, ethnic group), However, other characteristics or variables found in the literature to be important are not

collected by the HES-PROMS dataset. For example, previous evidence has shown an association between higher BMI and poorer self-reported health following a THR or TKR (see for example, Buirs et al. (2016)). It was not possible to control for this association, as the HES-PROMS dataset does not collect data on BMI or the components of it. Equally there are other factors that were identified in Chapter 1 that have been shown to be associated with differences in health outcomes such as other lifestyle factors, levels of air pollution or, where individuals lived could not be controlled for in the models in this Chapter.

One of the disadvantages of using self-reported data is that it is reliant on patients completing the questions accurately and fully (i.e. completing all the questions). As can be seen from the levels of missing data patients were more likely to complete the OKS and OHS sets of 12 questions in the PROMS dataset than the EQ-5D-3L and EQ-5D VAS. This may be due to the OKS and OHS having been developed specifically for this group of patients, so are potentially more relevant to them. Whereas the EQ-5D-3L, EQ-5D VAS and general health are generic measures of HRQoL. As noted the EQ-5D-3L did not pick up the most extreme mobility issues that this group of patients is likely to have. A key strength of this work is that the study employed up-to-date missing data methodology to assess whether the results were any different with the missing data imputed using a chained method, so taking account of a larger sample of the population than having to exclude those who did not complete all the questions. The results showed a similar message with the imputted data, so providing more confidence over the results.

This case study was based on the population of WY. One of questions and potential limitations of focusing on a WY case study is how generalizable the results are to the rest of the UK and to countries outside of the UK. WY is one of six metropolitan counties in the UK, the others are Greater Manchester, Merseyside, South Yorkshire, Tyne and Wear and the West Midlands. These metropolitan counties predominantly cover urban areas. It can be seen from the results in Table 16 that 93% of the patients reside in what is classed an urban area and only 7% in rural areas. It is likely that the results will be more comparable to these five other large metropolitan areas than shire counties that are predominantly rural. One of the aims of using the ELSA data set in the next Chapter is to allow the study to make an assessment of how comparable the travel times are for individuals across different regions of the UK.

One of the strengths of this research, compared to other research included in the systematic review, was inclusion of both the home postcode of the patients and the hospital attended (from the HES data) and of health outcomes (from the PROMS dataset). One of the weaknesses of using this dataset was that it did not include any information on how patients have travelled to the healthcare facilities and the study relied on the large secondary dataset and didn't collect

any primary data on a sample of patients travel times, but a strength is that it did allow a greater exploration of some of the key components of a patients travel to hospital or the GP (e.g. their ability to walk or access vehicles).

3.5 Conclusions

This chapter has used the HES-PROMS dataset to analyse the association between travel times and distances to the GP and healthcare facilities for patients undergoing THR and TKR operations and health outcomes. It has identified that those patients living closest to the hospital and those furthest away (travelling > 30 minutes) had the worse health outcomes following the operation. The key findings that will be taken forward in the remaining chapters of this thesis are:

- Using the LSOA that the patient resides in vs. patient home postcode did not dramatically change the results, but knowing which hospital the patient attended did. This should be borne in mind for Chapter 4 given the analysis uses the nearest healthcare facility as a proxy for the healthcare facility attended.
- One of the key limitations of this analysis is the dataset did not collect information on how the patient travelled to the healthcare facility. As shown in this Chapter travelling by bus has a statistically significantly different travel burden associated with it compared to travelling by car. It is critical therefore to know more about how the patients are travelling.
- Chapter 3 has used a WY OA patient population that has undergone a THR or TKR. To understand more how generalizable these results are to the rest of the country it will be important in Chapter 4 to assess how similar the travel times and distances to healthcare facilities across the different regions are to this WY patient population.
- Chapter 3 has used travel time and distance as a proxy measure for transport accessibility to healthcare. It is important that the wider aspects of transport accessibility (ability to walk and access vehicles plus others) as part of GC are investigated further.
- Due to the small sample size of RA patients it was not possible to include the RA patients in all the analysis. The focus of Chapter 4 will be to include individuals with OA and RA in the analysis.

Chapter 4 will now present the results of the ELSA dataset focusing on OA and RA patients in England to explore further the health and wellbeing of this population and the associations between transport accessibility and health.

4 Chapter 4: England Case Study: Measuring the association between transport accessibility and health for individuals with OA or RA

4.1 Introduction

The previous chapter used the HES-PROMS dataset to explore the association between travel times to healthcare facilities and health outcomes for OA patients in WY who had undergone a THR or TKR operation. This chapter uses the English Longitudinal Survey on Ageing (ELSA) dataset to explore the health and wellbeing of individuals with OA and RA in England. It goes further than Chapter 3 by drawing on the detailed information collected on the transport preferences and mobility abilities of people with OA and RA (e.g. Do they have access to a car when needed?, Do they use public transport?, How easy is it for them to access the GP?). This chapter then uses this data to explore the associations between transport accessibility including the concept of 'ease of access' (discussed in Chapter 1) to healthcare using the nearest healthcare facility and health / wellbeing measures. This allows the thesis to explore in a greater depth the potential associations, whilst having a better understanding of how individuals travel to access healthcare facilities.

This chapter will describe the health and transport data available from the ELSA dataset (year 2012/13) for individuals with OA and RA. It will then discuss the methodology used to analyse the data. The results section will present the characteristics of those with OA and RA, a description of their health and wellbeing and what can be determined about their mobility levels. The health/ wellbeing and transport accessibility data is then used to explore the associations between transport accessibility and health for these two MSK groups. Results will be compared across the regions in England to assess how comparable they are. The chapter will then discuss the findings and draw out conclusions relevant for Chapter 5 and future work. This chapter contributes directly towards study objectives 2 and 3, which are:

- *Objective 2: To explore and document the healthcare and transport accessibility of patients with Osteoarthritis and Rheumatoid Arthritis.*
- *Objective 3: Develop statistical models to examine the associations between transport accessibility to healthcare and inequalities in health for individuals diagnosed with RA and OA.*

The ELSA dataset is described next.

4.2 ELSA data

4.2.1 Description of the ELSA data

The ELSA is a longitudinal dataset from a representative sample of ~10,000 survey participants in England living in the community who are > 50 years old. The survey began in 2002 (Wave 0) with the sample being drawn from respondents to the Health Survey for England (HSE) (NHS Digital, 2018c). Participants once included are followed through until end of life. The HSE was designed to monitor trends in the national health overtime starting in 1991 onwards. Participants in the HSE are selected at random by address in England. In order to maintain the sample size overtime additional participants have been included from the HSE in ELSA. This longitudinal dataset is now on wave 9 for which the interviews started in 2018. Waves of data are collected every two years. The findings presented in this thesis are based on the cross sectional analysis of wave 6 of the ELSA.

The dataset is freely downloadable from the UK Data Service website (UK Data Archive, 2018), which stores a range of available datasets including ELSA and HSE. This survey contains information about the participants including information about pensions, education, demographic characteristics, and access to a car, whether they use public transport, how fast they can walk (carried out every 2 years) and a nurse led interview (which take place every 4 years). A summary of the key health and wellbeing measures are shown in Table 44.

Table 44: Health and wellbeing measures included in the ELSA survey

Health Measure	Description
Assessed by a nurse	Body Mass Index (height and weight) , Blood pressure, Lung function, Walking Speed
Physical Health	Mobility, Physician Diagnosed Conditions (e.g. Osteoarthritis) , Falls/ Balance, Pain
Behavioral Health	Levels of Physical Activity, Smoking
Well-being	Self-Rated Health, Quality of Life (CASP-19), Satisfaction with life, Centre for Epidemiological Studies Depression scale (CES_D)

In order to preserve anonymity key geographical identifiers in ELSA are kept separate from the main dataset. The study required approval from the NatCen Social Research Institute to have access to the geographical variables of deprivation quintiles (measured using the index of multiple deprivation) and the easting northing coordinates of the study participants' homes

address. Access to these geographical variables required attending the NatCen data enclave in London to calculate the travel times and distances to the nearest healthcare facilities and access the deprivation quintiles. The resulting calculations (minus the identifying variables) were transferred electronically to the University and linked to the ELSA dataset. Approval was granted in December 2016, but due to issues accessing the data (issues with installing correct software to analyse the data at the enclave) the enclave was only accessed in December 2017 and the data transferred and linked in February 2018. This data was then linked to the main dataset using the unique individual identifiers, resulting in a dataset with distances and travel times to the nearest facilities for each ELSA participants (minus the geographical variable) and ELSA variables.

One advantage of the ELSA dataset is that, as a representative sample of the population living in the community in England over the age of 50, it includes data that can be considered at both a national level and within each of the regions of England (shown in Map 3). One of the potential limitations of the results from Chapter 3 was an understanding of how generalizable the data was from the WY locality to the other regions in England in terms of the distances and travel times patients would have to travel to access healthcare facilities. Using the ELSA dataset allows the thesis to review whether there are differences between regions. One of the key queries is how generalizable to other contexts is a policy of centralisation of services (e.g. centralising stroke care in London (Morris et al., 2014) compared to applying this same policy in WY). If the nearest hospital was shut in London would the alternative be of a similar distance away to someone in the same situation living in Yorkshire and Humberside? One of the more pressing concerns of the move to centralisation of services is that not all regions will be affected equally – exacerbating the potential impact on health inequalities.

4.2.2 Reasons for using the ELSA dataset

Initially the idea for the thesis had been to use the longitudinal qualities of this dataset linked to HES. When ELSA participants complete the two yearly cycle of questions they are asked whether they give their permission for their data to be linked to other datasets including HES. Prior to this study starting it was expected that the ELSA participants data linked to the hospital data (HES data discussed in Chapter 3) was going to be available. This would have provided longitudinal data on the participants linked to hospital attendance and treatment. When it became evident during the study that this data was not going to be released in the timeframe of the study (and is now expected to be released in the summer of 2019), the study was adapted to look separately at HES data with health data from the PROMS (the focus of Chapter 3) and ELSA. One of the limitations of using the HES-PROMS dataset for this study was that whilst it was possible to calculate the travel times and distances from the patient's home to the

healthcare facilities attended no information was available on how these patients travelled and it was limited to patients with OA that had either had a TKR or THR. The addition of the ELSA dataset, whilst a sample of the total population in England provided data on people with RA and OA (not just those that had had a THR or TKR) linked to health. The study selected to use Wave 6 of this dataset, as a cross sectional analysis, as it was granted permission to calculate the transport accessibility variables for wave 6, which included both the health data collected by the nurse (collected every four years) and corresponded to the same survey years (2012/13), as the WY case study in Chapter 3.

This is a new application for this dataset, as firstly, no previous study has used the gridlink reference of the home address to calculate how far people live from the nearest available healthcare facilities. Secondly, no studies have used this data to explore the association between distance / travel time to healthcare and health outcomes for people with OA/RA.

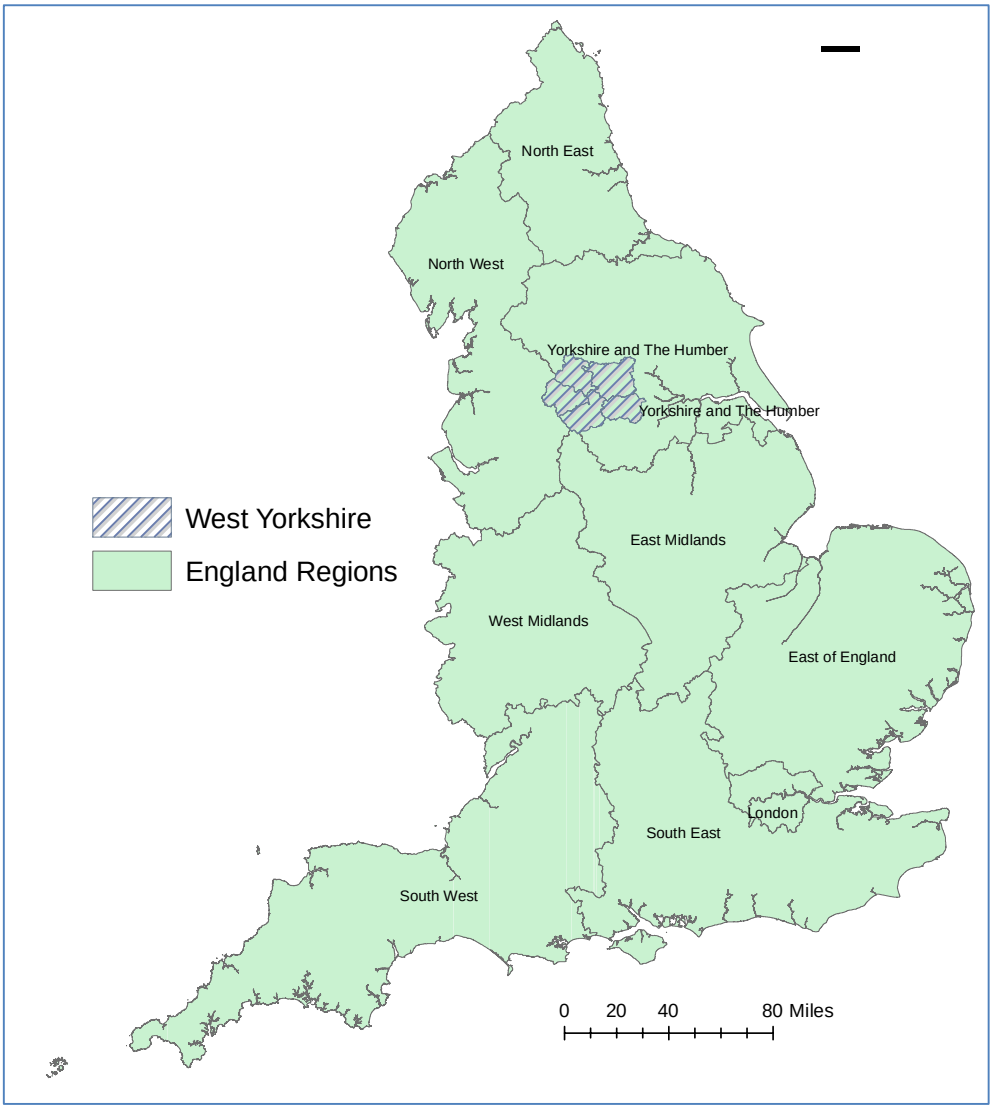
4.2.3 Determining the prevalence of OA and RA

Whilst no studies have used this data to explore the association between distance/ travel time for health outcomes for people with OA/RA work has been undertaken using ELSA by Imperial College London for Arthritis UK to produce an MSK prevalence calculator (Arthritis UK, 2017). Whilst calculating the prevalence of OA/ RA is not the main aim of this thesis, having a better concept of the numbers with MSK allows the thesis to consider the volumes of patients that might be affected in Chapter 5, which is focusing on changing where patients might access healthcare facilities.

There are a number of methods in the literature that have been developed to provide estimates of the prevalence of OA and RA in the population. Timmins and Edwards (2016) explored using spatial microsimulation techniques to develop small area estimates at the ward and local authority level for OA prevalence. Marshall et al. (2015) calculated new incidences of OA and the prevalence rates of OA for the residents of Alberta using the diagnosis codes for OA (ICD10 codes) in the medical records and insurance claims. They found that for the whole population (all ages) the prevalence rates were 86.6 for every 1,000 population (8.66%), which increased to around 60% for women who were over the age of 90 (Marshall et al., 2015). The MSK calculator developed by University College London (UCL) is summarized below with full technical report available from Adomaviciute et al. (2018). The team identified a number of risk factors for OA from the literature, which were matched to the data available within the ELSA dataset and data available on populations at the Middle Super Output Area (MSOA). The following variables were included: age, sex, ethnicity, education, socio economic status, BMI, physical activity, smoking and member at sports clubs/gyms. Some risk factors were excluded

as there was too much missing data within ELSA (e.g. housework/ gardening activity level). The tool has two levels of data. The first includes all cases of hip and knee OA and secondly, cases of severe hip and knee OA. Severe OA was separated from all OA by the answer to questions in the ELSA dataset of "Severity of pain most of the time" and "Difficulty walking ¼ mile unaided". If participants stated that they had pain most of the time, or had had previously a THR or TKR or they were unable to walk ¼ mile unaided then they would be classed as having severe OA.

Separate logistic regression models were run to identify the log odds of having or not having the different severity and type (hip/ knee) of OA for each of the risk factors using the ELSA data. Using these results the log odds were calculated for each possible permutation of risk factors (e.g. female, over the age of 60, who smoke, have a BMI > 30) by adding each of the individual log odds together. The log odds were converted to odds ratios (OR) and the prevalence for each combination of risk factors calculated by the formula (OR/ 1 + 0R). The same matrix with all the possible permutations and number of the population were created for each local area (at the MSOA) using the local data (e.g. number of females, over the age of 60, who smoke) taken from the census data, Office for National Statistics, household surveys and Sport England Active People Survey. The prevalence rates and number of people in each of the cells of the matrix were then multiple to give the prevalence rates. The estimates differ by locality based on the makeup of the local population. As discussed in Chapter 1 the majority of cases of OA are diagnosed after the age of 45, so the ELSA dataset and Arthritis UK Calculator provides a good match to the majority of the OA population. It does mean that they are less relevant for populations under the age of 50 with the disease. Another criticism is that some of the risk data was not available at the MSOA level and used Local Authority level data (e.g. the physical activity level and gym membership which was available at a local authority level), so was less local level specific. The calculator provides an initial starting point for exploring regional differences in OA. The results from applying this calculator for England and the WY districts are provided in Table 45. The results from using the Arthritis calculator have shown that the estimated prevalence of these two MSK diseases does vary across England.



Map 3: West Yorkshire and England Regions (source: boundary data ONS (2012))

The OA MSK calculator estimates that 10.9% of the population in England had signs of OA in the hip, WY at 11.1% is higher than the England average. Focusing on the districts of WY (considered in Chapter 3) Leeds has the lowest estimated prevalence of all categories of OA in WY (including a lower rate than England as a whole). Bradford has the highest estimated prevalence rates of OA with 11.7% of the population showing signs of hip OA and 3.7% having severe hip OA. The MSK calculator for RA draws on a number of datasets including ELSA and uses the Clinical Practice Research Datalink (CPRD) (Gardiner et al., 2017). There is a similar pattern to the OA results with the Leeds district having the lowest estimated population prevalence of RA in WY. It is worth noting that due to the larger population in Leeds the MSK calculator estimated that there are 5,331 cases compared to Calderdale which has the highest population prevalence, but only 1,551 cases of RA. West Yorkshire as a whole has lower population prevalence than England, but this is predominantly due to the lower population prevalence rates in the district of Leeds.

As can be seen from Table 45, there is variability depending on area and therefore variability in demand for services.

Table 45: Estimated prevalence of hip and knee OA and RA (% population)

	Hip OA	Severe hip OA	Knee OA	Severe knee OA	RA
England	10.9 %	3.2 %	18.2 %	6.1 %	0.84 %
West Yorkshire (WY)	11.1 %	3.3 %	18.6 %	6.3 %	0.81 %
Bradford	11.7 %	3.7 %	19.7 %	7.1 %	0.82 %
Calderdale	11.6 %	3.4 %	19.2 %	6.6 %	0.87 %
Kirklees	11 %	3.3 %	18.3 %	6.3 %	0.86 %
Leeds	10.6 %	3 %	17.5 %	5.6 %	0.76 %
Wakefield	11 %	3.2 %	19.1 %	6.3 %	0.83 %

Source: Calculated from Arthritis UK (2017).

4.3 Data and Methods

This chapter uses a range of methods to explore the data. Firstly, descriptive statistics are used to describe who the individuals with OA and RA are, their health and wellbeing and transport options available to them. Statistical models are then used to explore further the associations between transport accessibility (measured using travel time / distance and the results of the questions from the ELSA survey of – 'How easy is it to access the GP/ Hospital?') and health/ wellbeing. Finally, descriptive statistics are used to compare between the results for the different regions in England. Once the study had access to the transport and deprivation data and had linked it to the Elsa dataset and had stored it securely in the University's encrypted drive there were a number of stages to the process for analysing the data. These are split into four section:

Section 4.3.1: Health Outcomes

Section 4.3.2: Transport and travel times/ distances/ ease of access to the healthcare facilities

Section 4.3.3: Other explanatory / predictor variables

Section 4.3.4: Developing the statistical models

4.3.1 Health Outcomes

The overriding aim of this chapter is to identify those ELSA participants that have OA or RA and then explore in greater detail whether there is an association between transport accessibility and health / wellbeing. The ELSA dataset includes a wide range of health and wellbeing

measures (including Self-Reported General Health, CASP-19 and CES-D), which are described below.

4.3.1.1 OA / RA diagnosis

To determine which participants had OA and which had RA (or both) the study used the following self-completed questions in the ELSA survey:

- *Have you been told by a doctor that you have arthritis?*
- *Which types of arthritis do you have?*

From these questions in wave 6 it was determined that 2,624 individuals (24.8%) reported that they had OA and 674 individuals (6.4%) reported that they had RA (92 had both). These participants were selected for inclusion in the study. It should be noted that this was a self-reported diagnosis and is therefore reliant on the survey respondent correctly answering the question and knowing whether or not they had arthritis. As described in Chapter 1 there is some level of disparity between those patients that have radiograph evidence of OA, clinical diagnosis, but do not self-report it when asked (Parsons et al., 2015).

The study also compared in some cases the complete ELSA population with the subgroup identified as having OA or RA to see whether any key differences could be identified. As shown above the ELSA dataset asks participants to self-report firstly, whether they have arthritis and then secondly, if they report that they have arthritis to state whether they have RA or OA. As noted in Chapter 1 OA does not simply refer to a homogeneous group of patients who all have the same issues. For example, some patients have OA in all of their joints (e.g. hip, spine, knee, and shoulder) and others are diagnosed with OA in one joint and others with radiographic evidence of OA, but no symptomatic diagnosis. For RA, whilst most patients have RA in their wrists, it can affect different joints. One disadvantage of the ELSA dataset is that it does not ask patients to specify where they have arthritis. For example, someone with arthritis in the hip is likely to have differing mobility issues to another individual having arthritis in the hands and the treatments will differ.

4.3.1.2 Self-Reported General Health

One of the key measures of health collected in the ELSA survey is self-reported general health. This is a commonly used subjective measure of health status. In ELSA it is measured on the 5 point Likert scale of Excellent, Very Good, Good, Fair and Poor using the question

"Would you say that your health is…"

It is the one question that is common to the PROMS dataset discussed in Chapter 3. It was included to allow a comparison with the results in Chapter 3 and can be compared with the results from the UK census.

4.3.1.3 CASP-19 Quality of Life

CASP-19 is a quality of life measure developed by Hyde et al. (2003) based on 19 questions in the domains of control (C) , autonomy (A) , self-realisation (S) and pleasure (P) and is reproduced in Table 46. This measure was included in this study due to the wider range of facets of an individual's life that it considers to create a measure of quality of life (compared to the single question used for the self-reported general health measure). Each question is scored on a 4 point scale (from 'Often' to 'Never') and there are a mixture of positively and negatively phrased questions. To create the overall score questions 1, 2, 4, 6, 8, and 9 (negatively phrased questions) are reverse coded and then all questions are coded, as follows 4 =0, 3=1, 2 =2, 1 =3 and summed to give the range 0 – 57, where 57 represents the highest level of quality of life and 0 complete absence of quality of life. This quality of life measure has been previously used in a number of studies including French et al. (2015), where it was used to focus on how quality of life changed with age for individuals with and without OA in an Irish national sample, which reported that the CASP-19 score was found to decline with age and was lower at each age band for those individuals that were identified as having OA compared to those who did not have OA.

Table 46: CASP-19 questions

Q		Questions	Often Sometimes Not Often Never 1 2 3 4
C	1	My age prevents me from doing the things I would like to	
	2	I feel that what happens to me is out of my control	
	3	I feel free to plan for the future	
	4	I feel left out of things	
A	5	I can do the thing I want to do	
	6	Family responsibilities prevent me from doing what I want to do	
	7	I feel that I can please myself what I do	
	8	My health stops me from doing things I want to do	
	9	Shortage of money stops me from doing things I want to do	
S	10	I look forward to each day	
	11	I feel that my life has meaning	
	12	I enjoy the things that I do	
	13	I enjoy being in the company of others	
	14	On balance, I look back on my life with a sense of happiness	
P	15	I feel full of energy these days	
	16	I choose to do things that I have never done before	
	17	I feel satisfied with the way my life has turned out	
	18	I feel that life is full of opportunities	
	19	I feel that the future looks good for me	

Source: (Hyde et al., 2003)

4.3.1.4 Centre for Epidemiologic Studies Depression Scale (CES_D)

The CES-D was developed by Radloff (1977) to measure depressive symptoms in the general public. This measure of wellbeing was included in the study, following evidence from studies including, Handley et al. (2014) and Skarsvag and Wynn (2004) that there is a distance decay effect in attending psychiatric services (fewer individuals attend) the further they live from the practices), which may have an effect on health outcomes including depressive symptoms. McManus et al. (2016) described the results of the UK based Adult Psychiatric Morbidity Survey completed in 2014, which identified that 17% of adults over the age of 16 met the criteria for one of the common mental disorders. The CES_D started as 20 questions measured on a 4 point scale. A shorter version using yes/ no answers to 8 questions is included in ELSA and is recreated in Table 47. The questions that the ELSA participants answered are a mixture of positively and negatively phrased questions. If the participant answers yes to the negatively phrased questions or no to the positively phrased questions (4 & 6) a score of 1 is given and these are then summed to generate a score between 0 (no depressive symptoms) and 8 (maximum depressive symptoms). Studies such as White et al. (2016) have used a cut off of ≥3, as the diagnostic criteria for 'caseness' in depression using the 8 question CES_D. The models will be used to explore whether differences in transport accessibility are associated with this dichotomised score of < 3 depression symptoms vs ≥3 depression symptoms.

Table 47: CES-D Questions in ELSA

Now think about the past week and the feelings you have experienced. Please tell me if each of the following was true for you much of the time during the past week		Y	N
1	You felt depressed		
2	You felt that everything you did was an effort		
3	Your sleep was restless		
4	You were happy		
5	You felt lonely		
6	You enjoyed life		
7	You felt sad		
8	You could not get going		

Source: Adapted from NatCen (2014)

The three health and wellbeing variables described above are the key measures that will be included separately to assess whether transport accessibility is associated with differences in health and wellbeing.

4.3.2 Transport and travel times, distances and ease of access to the healthcare facilities

The ELSA dataset contains a wide range of data on how people travel and whether they have any mobility issues (e.g. difficulties walking). Questions include whether participants have access to a car or van when needed (either as the passenger or the driver), whether they use public transport (and if not why not) and whether they have used the PTS. For example, the following key questions about ability to walk and how far are asked:

- *How difficult it is for them to walk ¼ mile unaided (using the responses of no difficulty, some difficulty, much difficulty or unable to)?*
- *Do they have difficulty walking 100yrds? (using the responses of yes or no)*
- *How quickly can they walk (with a nurse measuring how long it takes them to walk 2.44 metres)?*

One of the consequences of these two MSK diseases is that pain in the joints can make movement more painful and therefore have a major impact on mobility levels and how far individuals can walk. Studies such as Vaughan et al. (2017) have reported on one particular consequence of this, which is that barriers to mobility for people with or at risk of OA have higher risks for reduced community participation. Reduced community participation then affects other areas of an individual's lives particularly when referencing back to the measures such as CASP-19, where one of the questions is "I enjoy being in the company of others".

This thesis included studies in Chapter 2 that had measured the travel times and distances to healthcare facilities. One of the main limitations of this methodology is that it is potentially too simplistic a measure to capture the true difficulties involved in getting from A to B especially in a cohort of patients that can have significant mobility issues, as described using the GC function in Chapter 1. To provide an example, we could have individual A who lives close to the hospital (less than 1 mile), lives alone, does not have a car and has a poor level of mobility, so could not walk there compared to individual B who lives 20 miles away, but has a car and someone who could drop them at the door of the hospital so they would not have to walk. The level of difficulty of getting to the hospital for individual A and B are not the same and there may be a worse impact on the health outcomes from the difficulty of travelling for individual A - who lives closer. Individual A is likely to have a higher GC value and be more elastic in their response to changes in transport accessibility to get to the healthcare facilities.

There are two questions in ELSA that perhaps better capture this broader issue. Participants are asked:

- *How easy is it for you to access the GP?*
- *How easy is it for you to access the Hospital?*

The possible responses are; Very Easy, Quite Easy, Quite Difficult, Very Difficult, and Unable to Go. Including the responses to these two questions should be a better representation of these unobserved factors that cannot be captured using a road network or travel time measure.

4.3.2.1 Calculating the travel times and distances to the nearest healthcare facilities

In addition to these transport variables the study calculated the distances and travel times (road network and straight-line) to the nearest GP, hospital with rheumatology department, A & E and bus stop using the gridlink coordinates of the participants home).The study calculated the travel time and distances at the NatCEN data enclave. This involved installing ArcGIS 14.2 on the computer in the enclave and forwarding the ITN network files (discussed in section 3.2.3.2). The files with a complete set of geocoded GP locations, rheumatology departments, A & E departments and bus stop locations across England, were transferred to the enclave. The GP locations were accessed through the EPRACCUR file downloaded from (NHS Digital, 2016a), the A& E locations and rheumatology departments across England were downloaded from (NHS Digital, 2017)and the bus stop data was downloaded from the Public Transport stop data for England from the Traveline National dataset (TNDS, 2016).

The network analyst tool in ArcGIS was used to calculate the travel times and distances for each of the ELSA participants for wave 5 and wave 6. It was not possible to install the Visography Tracc software at the NatCEN data enclave and so the decision was made to not calculate the bus travel times for this dataset. This data was linked back to the archived ELSA dataset using the unique study participant identifiers. Unlike the previous analysis outlined in chapter 3 the geographical data included where the participant lived, but not hospital attended or registered GP, similar to a large number of the studies described in Chapter 2 (e.g. Anderson et al., 2013; Schroen and Lohr, 2009).

4.3.3 Other Explanatory/ Predictor Variables

ELSA includes a large number of variables including a number of which were identified in Chapter 1 as being associated with health inequalities. The study wanted to include the key variables in the models described in Chapter 3 for comparisons plus additional variables collected in the ELSA dataset that had been identified in the literature, as being associated with health outcomes for individuals with OA and RA. The explanatory/ predictor variables considered are summarized in Table 48. For OA Age has been shown to be a potential explanatory factor, with

studies identifying that incidence of OA increases with age especially after age 50 years (Blagojevic et al., 2010). Blagojevic et al (2010) also showed evidence that whilst for OA in the hip there was no evidence of differences by gender, females were more likely to suffer from OA in the knee and OA in the hand. Studies in the UK have reported that patients with OA who need a THR or TKR in the most deprived groups are less likely than those in the least deprived groups to have a joint replacement (Judge et al., 2010), so potentially leading to difference in self-reported health outcomes if joint replacements are delayed. It is documented in the UK that individuals from non-white groups have poorer health than people from white groups, with individuals living in the UK originally from Bangladeshi having the poorest health (Nazroo, 2014; Evandrou et al., 2016). Smith et al. (2017) found that ethnic minorities were less likely to receive a THR or TKR than their white counterparts. There is the potential for health outcomes to also vary by education levels, as shown by the study by Davies et al. (2018) who found that staying longer in education reduced the risk of diabetes and mortality rates. Whilst smoking status was considered as a variable in the model, studies have shown conflicting evidence about whether smoking represents no effect or has a protective factor in development of arthritis (Blagojevic et al (2010). Smoking was not included due to the level of missing data.

Whilst a number of the variables have been shown to be associated with differences in health there is less evidence of whether they also affect the independent variable of transport accessibility (potential confounders). It should be expected that access to a car and difficulty walking would be potential confounder variables, as they could affect both the health outcome and transport accessibility to healthcare facilities.

Table 48: Potential Explanatory / Predictor Variables

Variables	Categories	Included in Chapter 3?
Gender	Female, Male	YES
Age	< 60, 60 – 80 and > 80	YES
Ethnicity	White, Other	YES
Deprivation Quintiles (%) (1 = least deprived)	1 – 5	YES
Comorbidities (%)	0, 1-2 and >2	YES
Living Arrangements (%)	Living alone vs Married/ Cohabiting	YES
Education (obtained)	Degree or equivalent, below a degree, Foreign/ other and no qualification	NO
Smoking status (%)	Current vs Ex Smoker vs Never	NO
Access to a car	Access when needed / no access when needed	NO
Difficulty Walking 400m	No difficulty, some, much/unable	NO

One of the variables that was not directly available from the dataset was a comorbidities index. Documenting the diseases and health is an important part of the ELSA survey, but it does not

produce its own composite measure. This was an important variable to control for, as the more comorbidities a person has the increased likelihood they will attend healthcare facilities more frequently and have poorer health / quality of life (Hutchinson et al., 2015). The results of the models in Chapter 3 showed that the more comorbidities that an individual has the worse their health outcomes.

For this study a proxy measure was created using the categories included in the Charlson comorbidity index and data available in ELSA. Not all categories were covered in ELSA, as shown in Table 49 (e.g. ELSA does not collect information on renal disease). A score of 1 was allocated for each comorbity that was recorded (either as a confirmed previous diagnosis or a new diagnosis). These scores were summed and grouped into 3 categories: 0 comorbidities, 1-2 comorbidities and >2 comorbidities, whilst not a perfect match for the Charlson index it does allow the thesis to control for some of the main comorbidities (e.g. Dementia and Diabetes).

Table 49: Charlson Index Categories and data available in ELSA

Charlson Index Categories	In ELSA ?	ELSA Description	Included (score)
Myocardial infarction	Yes	Heart Attack	1
Congestive heart failure	Yes	Congestive Heart Failure	1
Cerebrovascular Disease	Yes	Stroke	1
Dementia	Yes	Dementia	1
Chronic Pulmonary Disease	Yes	Chronic Lung Disease	1
Connective Tissue / Rheumatic Disease	Yes	Rheumatoid Arthritis	1
Diabetes without complications	Yes	Diabetes	1
Diabetes without complications	Yes		
Cancer	Yes	Cancer	1
Metastatic carcinoma	No		
Peptic Ulcer Disease	No	-	-
Mild Liver Disease	No	-	-
Moderate or severe liver disease	No	-	-
Paraplegia and Hemiplegia	No	-	-
Renal Disease	No	-	-
Peripheral Vascular Disease	No	-	-
AIDS/HIV	No	-	-

Source: Adapted from (Charlson et al., 1987)

In order to determine which of the available variables to include the study looked at the correlations between variables (strength of association). Including two highly correlated variables, as independent variables in the regression analysis will cause problems with collinearity. This has a disabling effect on the coefficient estimates for the independent variable, as it causes an increase in the standard errors of the coefficients, which can make some variables incorrectly statistically insignificant. Pearson's correlation coefficient and Phi Coefficient were employed to assess the strength of association between the variables (test for collinearity) (Hinkle et al., 2003). The results are shown in Table 50, with Table 13 (see Chapter 3) providing

a guide on how to interpret the results. As can be seen from the table the highest correlation was between walking ability and comorbidities with a positive correlation of 0.33, as shown in Table 13 this fits it into the category of low correlation. One area that was potentially expected to have a high correlation was between deprivation and education level, but whilst positive was in the negligible category at 0.22. No variables were excluded on the basis of the correlations.

Table 50: Correlations between covariates (using Pearson's Correlation Coefficient and Phi Coefficient)

	Travel Time to GP	Access to a car	Difficulty walking	Gender	Age	Deprivation	Living arrangements
Travel Time to GP	1						
Access to a car	-0.1945*	1					
Difficultly walking	-0.0617*	0.2590*	1				
Gender	-0.0206*	0.0972*	0.0487*	1			
Age	-0.0228*	0.1901*	0.2853*	-0.0250*	1		
Deprivation	-0.1945*	0.2224*	0.1643*	0.0093	-0.0191*	1	
Living Arrangements	-0.1040*	0.3663*	0.2204*	0.1573*	0.2242*	0.1382*	1
Comorbidities	-0.0278*	0.1463*	0.3314*	-0.0481*	0.1970*	0.1015*	0.1152*
Ethnic Group	-0.0738*	0.0192	0.0189	-0.0042	-0.1011*	0.0994*	-0.0199
Education	-0.0735*	0.2110*	0.2318*	0.1226*	-0.0184	0.2242*	0.1427*
Ease of Access to GP	0.0139	0.2174*	0.3067*	-0.0183	0.1266*	0.1124*	0.1428*

	comorbidities	Ethnic Group	Education	Ease of access
Comorbidities	1			
Ethnic Group	0.0031	1		
Education	0.1266*	-0.0184	1	
Ease of Access to GP	0.1496*	0.0744*	0.1240*	1

(Legend * p <0.0.5)

The study used the entry approach (including all explanatory variables at once) or a priori knowledge to determine variables to include in the regression models, as was used for the models in Chapter 3. All included variables had been identified in the literature as potential predictors of differences in health outcomes for this group in the population and had been assessed for collinearity. All variables that were included either had evidence of being associated with the dependent variable (health outcome) or were being tested by this research (e.g. travel times and access to a car). An alternative approach that could have been used to determine which variables to include is the stepwise approach whereby variables are included

or removed from the model based on whether they improve or reduce the predictive ability of the model using a computer algorithm. However, there has been criticisms of stepwise approaches, as it has the potential to over fit the model and include variables that have no associations to the outcome measure (Derksen and Keselman, 1992; Babyak, 2004) and so was not used here.

4.3.4 Modelling the data

The data from the ELSA dataset has a variety of different health measures and transport outcomes all of which require different statistical models. A summary of the data and the different types of statistical models are provided in Table 51. Three main types of models are employed – ordinary least squared or linear regression (OLS), Binary logit regression and ordered logit regression. In addition, where the ordered logit regression model is not suitable (described below) the generalized ordered logit model is used. This section will briefly describe each of these models

Table 51: Health/ wellbeing Outcomes and statistical methods

Outcome Variable	Type	Categories	Model
Access to a car when needed	Binary	0 = access 1 = no access	Binary logistic regression
Ease of access to the GP/ Hospital	Ordered categories	1 = very easy 2 = quite easy 3 = quite difficult 4 = very difficult/ unable to go	Ordered logit regression. Brant test Generalised ordered logit model
CASP-19	Continuous	0 - 57	Linear regression (OLS)
CES_D	Binary	0 = not 'caseness' 1 = 'caseness'	Binary logistic regression
General Health	Ordered categories	1 = Excellent/ V.good 2 = good 3 = fair 4 = poor	Ordered logit regression. Brant test Generalised ordered logit model

The multiple linear regression (ordinary least squares – OLS), was used for modelling the association between CASP-19 and transport accessibility. The formula for the OLS is provided in Equation 6.

Equation 6

$$y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n x_n + \varepsilon \qquad where\ \varepsilon \sim N(0, \sigma^2)$$

Where:

y = Health/ wellbeing dependent variable

$\beta_0 = the\ intercept$ *(constant)* $\beta_1 \rightarrow \beta_n = independent\ variable\ coefficients$ $\varepsilon = error$

In order to apply an OLS model to the data the study is making the parametric assumption that the data comes from a population with a normal distribution. This assumes that the values from the population (from which the sample was taken) are normally distributed. The central limit theorem states that "given random and independent samples of N observations each, the distribution of sample means approaches normality as the size of N increases, regardless of the shape of the population distribution" (Anderson (2010),p 1). It is widely reported that 30 is the minimum sample size required to satisfy this 'large' N (ibid). In addition to the study having a large sample size and a linear relationship the following tests where run to see whether it was suitable to apply an OLS to the data. These were:

- Are the residuals (error terms) normally distributed? This was tested by plotting the residuals as a histogram and including a normal curve for comparison.
- Are the residuals homoscedastic? This was tested by plotting the residuals against the predicted values. For the residuals to be homoscedastic there should be no pattern to the data. Where the residuals were found to be heteroscedastic (patterns identified) this was controlled for using robust errors in the models to correct for this
- Is there any multicollinearity? Are the predictor variables highly correlated with each other? This was tested by calculating the VIF.

The tests were applied to all the models and the OLS was decided as the approach to be used for the CASP19 data. An example of the tests for the CASP19 model focusing on ease of access to the hospital, as the transport accessibility are shown in Figures 38 to assess whether the residuals are normally distributed, and Figure 39 to allow an assessment of whether the residuals are homoscedastic and in Table 52 the results of the VIF to test to see the levels of multicollinearity between the variables in the model, which averaged at 1.4, so low amounts of multicollinearity.

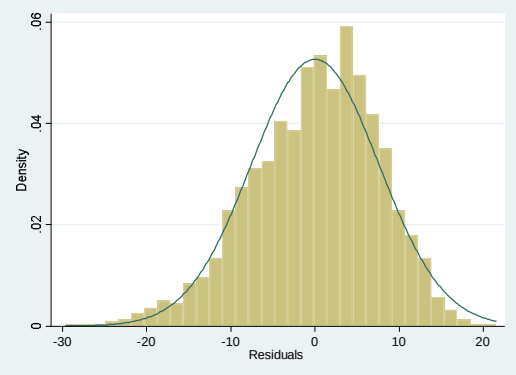


Figure 38 Kdensity plot of the residuals (CASP19 ease of access to hospital for OA

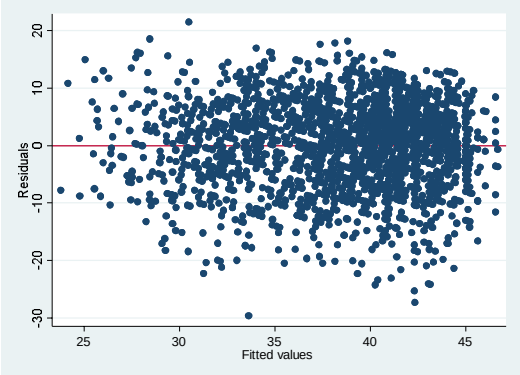


Figure 39: Scatter plot of residuals vs fitted values (CASP19 ease of access to hospital for OA)

Measures of fit can be used to assess how well the models fit the data. In terms of evaluating the fit of the results of the OLS, the study has used the R^2, which is a measure of how close the real data points are to the fitted regression line. An R^2 of 1 indicates that the OLS model explains all the variability. It is often used in the health economics literature due to its intuitive interpretation on a scale between 0 and 1. For example an $R^2 = 0.18$ can be interpreted as 18% of the variation in the dependent health variable can be explained by the independent variables in the model. The study also included the Root Mean Square Error (RMSE) in the results tables to assess the fit of the model, which is the square root of the variance of the residuals. It can be interpreted as the standard deviation of the unexplained variance and is a good measure of how accurately the model predicts the outcome. Lower values of RMSE indicate a better fit. Other measures that could also have been used to assess the fit of the model are the adjusted R^2, which adjusts the R^2 based on the number of predictors in the model, so that the R^2 does not simply get larger because more variable have been added.

Table 52: Testing for Multi collinearity (CASP19 ease of access to hospital model for OA)

	Variable	VIF
Access to a car		1.29
Level of ease of access (base = Very Easy)	Quite Easy	1.26
	Quite Difficult	1.26
	Very Difficult/ Unable to go	1.24
Living arrangements (base = cohabiting)	Alone	1.20
Age Groups (base = < 60)	60 – 80	1.43
	> 80	1.50
Deprivation Quintiles (1 = least deprived)	2	1.55
	3	1.52
	4	1.48
	5	1.49
Gender		1.09
Comorbidities (base = none)	1-2	1.08
	>2	1.08
Education (Base = A degree)	Below a degree	2.14
	Foreign / Other	1.60
	No Qualifications	2.18
Ethnic Group (base = Non white British)	White British	1.02
Average VIF		1.40

In terms of the coefficients the study is assessing whether the p-values are <0.1, < 0.05 and < 0.001. This means that the null hypothesis ($H_0 : \beta 1 = 0$) can be rejected ($H_1 : \beta 1 \neq 0$) if the p values are less than the thresholds. For example, if the p value for the coefficient for an independent variable was 0.04 then the null hypothesis could be rejected at the 10% and 5% significance level, but not at the 0.1% significance level. Having a result that is statistically significant at the 5% versus 10% level the less likely the model will conclude an association between the dependent variable and the independent variable, when there is no association. The literature has focused predominantly on statistically significance levels of below 0.05 ($p<0.05$), which indicates a 5% risk of making this type of error widely attributed to Fisher (1950). A number of authors have commented that the $p<0.05$ is somewhat an arbitrary threshold, that services a general purpose (Stigler, 2008). One of the criticism of this threshold is that using just $p<0.05$ means that those results with a p value $p<0.049$ are deemed statistically significant whilst those at $p<0.051$ are not. It is common practice in the field of health economics to present a range of p values (e.g. $p<0.1$, 0.05 and 0.01) to show the range at which different variables are statistically significant.

OLS models are not suitable for data that is binary (e.g. having / not having access to a car), as it would violate the assumption that there is a linear association, a better fit are binary logistic regression models. In logistic regression the outcome Y (dependent variable), which is a binary 0 or 1 outcome is transformed using a logit transformation (see equation 7) so becomes In $\left[\frac{\mathrm{p}}{1-\mathrm{p}}\right]$ rather than Y, as used in the OLS equation shown in equation 5.

$$ln\left[\frac{p}{1-p}\right] = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n + \varepsilon \qquad \textit{Equation 7}$$

Where:

- *ln = the natural log of the odds that Y equals one of the binary categories (0 /1)*
- $\left[\frac{p}{1-p}\right]$ *= the odds ratio (whereby p = the probability of an event occurring e.g. person having access to a car when needed or probability Y = 1))*
- β_0*= the constant*
- $\beta_1 \rightarrow \beta_n$ *= the independent variable coefficients for the n independent variable* x_1 to x_n

The results are interpreted in a similar way to the OLS model. It is not possible to use the R^2 to assess model fit, but a pseudo R^2 can be determined, which allows comparisons between the model with and without covariates (unadjusted and adjusted). The interpretation of the p values is the same. A p value of ≤ 0.1, 0.05, 0.001 allows you to reject the null hypothesis that the independent variable coefficient equals zero (H_1 : β1 ≠0) at the 10%, 5 % and 0.1% levels and conclude that there is a statistically significant association between the independent variable and the dependent variable at that level.

Binary logit regression models are a good fit for data with binary outcomes, but other measures that are included in this study have ordinal data with >2 categories. For example the measures of self-reported general health and ease of access to a GP or Hospital (Very Easy, Quite Easy, Quite Difficult and combined Very Difficult /Unable to Go). The method commonly used to model these types of data is the ordered logistic regression model. It caters for ordinal dependent variables (such as the 5 point Likert scales used to measure ease of access and self-reported general health), where the data is ordered. The formula is shown in Equation 8, where the unobserved (latent) variable y* is a function of the constant and independent variables, as for the OLS, but that the error term is assumed to have a logistic distribution.

$$y_i^* = \beta_0 + \beta_1 X_1 + \beta_2 \beta_2 + \cdots + \beta_n X_n + \varepsilon_i, \qquad \varepsilon \sim logistic(0, \frac{\pi^3}{3}) \qquad \textit{Equation 8}$$

The continuous unobserved (latent) variable y* is divided into observed, ordinal categories (in this study 4 categories) using the thresholds of τ_0 to τj.

$y_i = j \quad if\ \tau_{j-1} \ll y_i^* < \tau_j \ \ for$ j = 1 to 4

Where τ_0 = - ∞ and τj = ∞ . For the ease of access to the GP/ hospital the observed categories determined by the model are:

$$y_i \begin{cases} 1 = Very\ Easy & if\ \tau_0 = -\infty \leq y_i^* < \tau_1 \\ 2 = Quite\ Easy & if\ \tau_1 \leq y_i^* < \tau_2 \\ 3 = Quite\ Difficult & if\ \tau_2 \leq y_i^* < \tau_3 \\ 4 = Very\ Difficult..Unable & if\ \tau_3 \leq y_i^* < \tau_4 = \infty \end{cases}$$

One of the assumptions of the ordered logit regression model is that there is no difference in the coefficients produced when comparing between the different outcome categories i.e. the proportional odds are the same of going from Very Easy to Quite Easy and Quite Difficult to Very Difficult for example. The Brant Test (Brant, 1990) is used to assess whether this assumption holds , i.e. whether any deviations from the model (differences when comparing between categories) are bigger than would be expected by chance. If the assumptions do not hold then the option available that is a better fit for the data would be to use a generalized ordered logit model, which updates the model to allow for different coefficients (betas) between differing categories (Williams (2006)). As for the binary logistic regression a pseudo R^2 can be calculated to assess the fit of the model with and without the covariates included and p values to test the hypothesis.

For each of the methods the statistical model was run first unadjusted (the dependent health / wellbeing variable and independent transport variable) and then adjusted for the identified included other explanatory variables. Descriptive techniques are used to summarize the key differences between the different regions, depending on the type of data.

4.4 Results

In total there were 10,566 individuals from wave 6 of ELSA included in the case study. Of these 2,624 (24.8%) reported that they had OA and 674 (6%) had RA. A summary of the individuals is provided in Table 53 showing the complete ELSA population and then those that self-reported that they had OA or RA separately. On average individuals with OA were more likely to be female, older, white British, living in more deprived residential areas, were less likely to have never smoked and more likely to have no educational qualifications and be living alone compared to the complete ELSA sample. These trends were the same for the population diagnosed with RA compared to the complete ELSA sample. Ninety-two (0.9%) individuals self- reported that they had both RA and OA.

The OA sub group had a higher proportion living in the top two most deprived quintiles compared to the ELSA population and had a higher proportion of individuals who had categorized themselves as being White British. The OA group had a lower proportion of the population who were current smokers compared to the total ELSA population. There was a lower proportion of the OA sub group with a degree or equivalent qualifications and higher proportion with no qualifications than the ELSA population.

In terms of comorbidities we can see that 31.2% of the ELSA population with RA have more than two comorbidities compared to only 5.2% in the total ELSA population, showing that the comorbidity index developed by the study is able to pick up some key differences. Individuals with RA are also more likely to have no qualifications, with 38% of the RA sub group not having any qualification compared to the total population at 25.4% and are also less likely to hold a degree or equivalent qualifications. In terms of smoking individuals with RA are more likely to either be a current smoker or ex-smoker compared to both the OA subgroup and total ELSA population. They are also more likely than the OA population and total population to be living in areas that are classed as being in the top two most deprived quintiles. Compared to the percentage of women in the ELSA population there are a higher number of females in the RA population that have self-reported that they have RA. A number of differences have therefore already been observed from the descriptive data.

Table 53: Who are the individuals with OA/RA?

	Categories	All	OA	RA
Total	Sample	10,566	2,624	674
Sex (%)	Female	55.2 %	65.7 %	62.8 %
Age (%)	< 60	31.6 %	18.1 %	21.8%
	60 – 80	57.8 %	67.7 %	61.7 %
	> 80	10.5 %	14.2 %	16.5 %
Ethnicity (%)	White	96.2 %	97.5 %	95.0 %
Deprivation Quintiles (%) (1 = least deprived)	1	25.0 %	23.1 %	17.3 %
	2	25.0 %	23.8 %	23.4 %
	3	20.9 %	21.4 %	21.0 %
	4	16.7 %	17.5 %	20.8 %
	5	12.4%	14.1 %	17.6 %
Comorbidities (%)	0	74.6 %	73.3 %	-
	1 -2	20.2 %	20.4 %	68.8 %
	>2	5.2 %	6.4 %	31.2 %
Smoking status (%)	Current	12.5 %	10.2 %	14.2 %
	Ex	51.9 %	55.5 %	55.6 %
	Never	35.7%	34.3 %	30.1 %
Education (obtained) (%)	NVQ4/NVQ5/degree or equivalent	17.7 %	14.6 %	11.2 %
	Higher ED below degree	13.6%	14.2 %	12.0 %
	NVQ3/GCE/A level equivalent	8.6 %	7.3 %	7.0 %
	NVQ2/GCE Olevel equivalent	19.0 %	18.3 %	16.6 %
	NVQ1/CSE other grade equivalent	4.1 %	4.3 %	4.2 %
	Foreign/ other	11.5 %	11.6 %	10.6 %
	No Qualifications	25.4 %	29.7 %	38.4 %
Living Arrangements (%)	Married or cohabiting	72.0 %	65.8 %	58.6 %

4.4.1 Does the health and wellbeing of individuals with OA/ RA differ?

4.4.1.1 Self-Reported General Health

The first self-reported health outcome measure that is considered is the self-reported general health question. The results for the total ELSA population and OA and RA subgroups are summarized in table 54. The table shows that whilst 12.1% of the total ELSA population would rate their health as Excellent only 5.5% of those with OA and 3.1% with RA would give the same rating indicating some levels of health inequalities between the different groups. At the other end of the scale 41.1% of those with OA and 51.1% of those with RA would rate their general health as Fair or Poor compared to 27% of the total ELSA population. In the RA group 45.8% reported that their health was 'Very Good' or 'Good' compared to 53.1% in the OA group and

compared to the census data collected in 2011 for the total UK population, where 81.4% of people in England reported their general health as either 'Very Good' or 'Good' (ONS, 2016a)

Table 54: Self-Reported General Health (percentage of total)

	Total ELSA population	OA	RA
Sample	9,945	2,542	646
Excellent	1,206 (12.1%)	140 (5.5%)	20 (3.1%)
Very Good	2,883 (30.0%)	509 (20.0%)	102(15.8%)
Good	3,144 (31.6%)	842 (33.1%)	194 (30.0%)
Fair	1,913 (19.2%)	710 (27.9%)	216 (33.4%)
Poor	799 (8.03%)	341 (13.4%)	114 (17.7%)

The data shows that there are some key differences in self-reported health between the general population over the age of 50 and those with OA or RA within ELSA. For the analysis focusing on the associations with health outcomes the data in the Excellent category, which had 20 individuals with RA and 140 individuals with OA was collapsed with the category of Very Good to create one category due to the small sample sizes, therefore reducing the number of categories from 5 to 4. This was justified on the grounds that the study wanted to compare those with better self-reported general health (Excellent & Very Good) to those with worse self-reported general health.

4.4.1.2 CASP-19

The second self-reported health measure was the CASP-19 in which 19 individual questions, are combined to produce a score of between 1 and 57. The distribution of scores for individuals with OA and RA are shown in Figure 40 and Figure 41. They show a high degree of variability of quality of life across the two subgroups, broadly representing a normal distribution. The average CASP-19 score for the OA sub group was 38.27 (CI 95% 37.89 – 38.65) and the RA subgroup 37.5 (CI 95% 36.71 – 38.30). There was some cross-over in the 95% CI between the two groups indicating that whilst the RA subgroup had lower average scores than the OA subgroup these were not statistically significantly different. Both groups had lower average quality of life scores than the complete ELSA group, whose average was 40.76 (CI 95% 40.57 – 40.95). With non-overlapping 95% confidence intervals indicating that the lower quality of life score represents a statistically significant difference between the complete sample and those identified as having OA or RA. On average the OA and RA subgroups reported lower quality of life using the CASP-19 measure than the full ELSA population

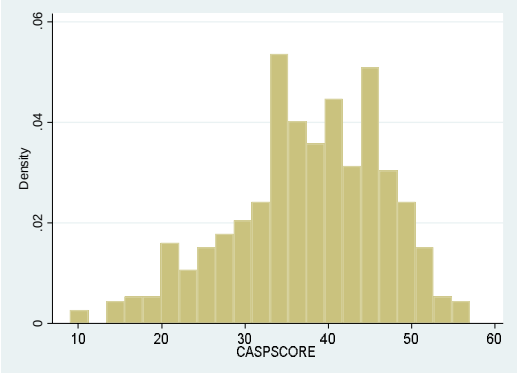


Figure 40: CASP-19 distribution for individuals with RA

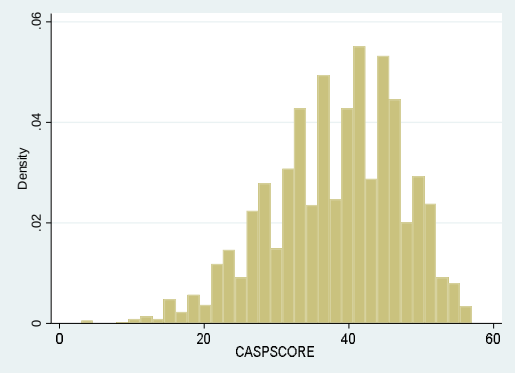


Figure 41: CASP-19 distribution for individuals with OA

4.4.1.3 CES_D

The third and final self-reported health measure was the CES_D measures of depressive symptoms in the population. For the CES_D the average score (out of 8) for the complete ELSA population was 1.35 (CI95% 1.32 – 1.39)). The OA subgroup had a higher average score of 1.77 (CI95% 1.69 – 1.86) and RA subgroup higher still at 1.97 (CI95% 1.80 – 2.14). The 95% CI indicate that there is some overlap between the OA and RA subgroups , so we could not be confident that the means differed, but no overlap when compared to the whole ELSA population. Using the cut off of ≥3, 30.9 % of individuals with OA and 35.2% of individuals with RA compared to 25.9% of the total ELSA sample fitted the criteria of 'caseness'. The CES_D dichotomised score (<3 and ≥3) is included as the dependent variable in the statistical models using CED_D

4.4.1.4 Summary of the three health outcome measures

A summary of the health and wellbeing measures is provided in Table 55 by subgroup and the total ELSA population. In terms of self-reported general health the full spectrum from *Excellent* to *Poor Health* is recorded. Compared with the total ELSA population the subgroup with OA were less likely to class their health as Excellent or good are more likely to have a lower CASP-19 score, and score on average lower on each of the CASP-19 domains. They were also more likely to be classed as having a higher number of symptoms of depression. For those with RA, they were on average in poorer self-reported general health than both those with OA and the complete ELSA population. Those with RA had on average the worst health and wellbeing, although there were overlaps between the mean values for the OA and RA subgroups indicating that the means were not statistically significantly different at the 95% confidence level. In terms of health status and measures there are health inequalities between the different groups.

Table 55: A summary of the health and wellbeing measures (numbers in brackets 95% CI)

Health Measure		All ELSA	OA	RA
Self - Reported General Health	Excellent	12.1%	5.5%	3.1%
	Very Good	28.99%	20.0%	15.8%
	Good	31.6%	33.3%	30.0%
	Fair	19.2%	27.9%	33.4%
	Poor	8.0%	13.4%	17.7%
CASP-19	Mean	40.8 (40.6 – 41.0)	38.3 (37.9 – 38.7)	37.5 (36.7 – 38.3)
	Control (0 – 12)	7.7 (7.6 – 7.7)	6.8 (6.7 – 6.9)	6.5 (6.3 – 6.8)
	Autonomy (0 – 15)	10.2 (10.1 – 10.2)	9.4 (9.3 – 9.5)	9.4 (9.2 – 9.6)
	Pleasure (0 – 15)	13.1 (13.0 – 13.1)	12.9 (12.8 – 13.0)	12.8 (12.6 – 13.0)
	Self-Realisation (0-15)	9.9 (9.8 – 9.9)	9.1 (9.0 – 9.3)	8.7 (8.4 – 9.0)
CES-D	Mean	1.35 (1.32 – 1.39)	1.8 (1.69 – 1.86)	1.97 (1.80 -2.14)
	% with a score ≥3	25.9%	30.9%	35.2%

4.4.2 Transport Results

4.4.2.1 Distances and travel times to the nearest facilities by car

The study derived the distances and travel times to the nearest healthcare facilities for the ELSA participants. The results for the road network distance and travel times using the home location are summarized in Table 56. In terms of accessing the nearest GP the average travel times across the whole ELSA sample was 3.53 mins, with a minimum of 0 mins and maximum of 26 mins. The OA subgroup had similar average travel times to the nearest GP, but the RA subgroup lived on average closer to their nearest GP. The 95% CI show that there are no statistically significant differences between the three groups in terms of travel times to the nearest GP. The same trends were true for the travel distances.

The travel times for accessing the nearest hospital with a rheumatology department were very similar for the three groups and the 95% CI overlapped suggesting that there were not any statistically significant differences in the means. The average travel times for the whole ELSA sample were 14.52 mins with a minimum of 0 mins and maximum of 86.18 mins. The results for accessing the nearest A&E showed a similar picture with average travel times of 16 mins for all three groups.

The subgroup of individuals who had self-reported that they had OA lived on average 1.2 miles from their nearest GP, 6.8 miles from the nearest hospital with a rheumatology department and 7.7 miles from the nearest A & E. The subgroup with RA lived on average 1.11 miles from the nearest GP, 6.85 miles from the nearest hospital with a rheumatology department and 7.62

miles from the nearest A & E. This compares with the WY case study in Chapter 3 of 0.88 miles from the nearest GP 4.44 miles from their nearest hospital Straight-line distance was included in the methods to compare with the results from the WY case study (but not included in Table 55). The calculations show that using a straight-line calculation instead of the road network distance underestimated the travel distance to the nearest GP by 35%, the nearest hospital by 27% and the nearest A & E by 25% (for all ELSA participants). With similar results for the OA and RA subgroups.

Table 56: Travel times and Distances to the nearest facilities (wave 6)

		All ELSA		OA		RA	
		Road Network (miles)	Road travel time (mins)	Road Network (miles)	Road travel time (mins)	Road Network (miles)	Road travel time (mins)
GP	Mean (sd)	1.19 (1.29)	3.53 (3.29)	1.18 (1.28)	3.5 (3.24)	1.11 (1.25)	3.35 (3.16)
	CI 95%	1.17 – 1.22	3.47 – 3.59	1.13 – 1.23	3.38 – 3.63	1.02 – 1.21	3.11 – 3.58
	Range	0 – 11.86	0 – 25.85	0 – 10.1	0 – 23.0	0 – 9.28	0 – 21.42
A&E	Mean (sd)	7.58 (6.10)	15.85 (11.07)	7.70 (6.16)	16.1 (11.09)	7.62 (6.39)	15.92 (11.48)
	CI 95%	7.47 -7.70	15.64 – 16.06	7.47 – 7.94	15.63 – 16.48	7.14 – 8.11	15.05 – 16.79
	Range	0.17 – 49.28	0.48 – 86.18	0.2 – 49.3	0.9 – 86.2	0.58 – 48.13	1.74 – 84.64
NHS Hospital	Mean (sd)	6.84 (5.62)	14.53 (10.28)	6.8 (5.56)	14.5 (10.14)	6.85 (5.88)	14.54 (10.73)
	CI 95%	6.73 – 6.94	14.34 – 14.73	6.58 – 7.01	14.07 – 14.85	6.40 – 7.29	13.73 – 15.35
	Range	0.002 – 49.28	0.001 – 86.18	0 – 49.3	0 – 86.2	0.53 – 48.13	1.74 – 84.64

The study calculated how far patients would need to travel to reach the second nearest facility if the nearest facility was not available. Where restructuring of healthcare services is being undertaken the implications of shutting the nearest facility or reconfiguring services so patients have to attend a different hospital for their treatment become more critical, where subsequent travel to healthcare maybe affected. The results showed that this would increase average travel distance to the GP for the OA subgroup by 0.96 miles and the RA subgroup by 0.86 miles. Access to the nearest A & E would increase from 7.70 miles to 29.42 miles for the sub group with OA (with one individual having to travel 126 miles to get to the second nearest A & E). If the nearest hospital with a Rheumatology department was shut or patients transferred to the second nearest this would increase the average travel distances from 6.8 miles to 13.36miles for those

in the OA sub group and from 6.85 miles to 12.89miles for the RA sub group (as shown in Table 56 and Table 57). For emergency travel to the A & E department the average travel time would go up by 13 minutes (assuming no congestion on the roads).

Table 57 Travel times and distances to the second nearest healthcare facility

		OA		RA	
		Road Network (miles)	Road travel time (mins)	Road Network (miles)	Road travel time (mins)
GP	Mean (SD)	2.14 (1.94)	5.52 (4.32)	1.97 (1.92)	5.19 (4.27)
	CI 95%	2.06 – 2.21	5.35 – 5.68	1.68 – 2.67	4.43 – 6.41
	Range	0 – 0.13	0.42 – 29.47	0.03 – 12.21	0.15 – 28.16
A&E	Mean (SD)	15.63 (9.53)	29.42 (16.80)	14.86 (9.51)	28.17 (16.80)
	CI 95%	15.27 – 15.99	28.77 – 30.06	13.39 – 17.67	25.51 – 32.96
	Range	1.38 - 67.58	3.17 – 126.12	1.67 – 57.99	4.75 – 101.26
NHS Hospital	Mean (SD)	13.36 (8.16)	25.70 (14.57)	12.89 (8.89)	24.86 (15.72)
	CI 95%	13.04 – 13.67	25.14 – 26.26	11.48 – 15.55	22.26 – 29.24
	Range	0.23 – 56.35	0.96 – 98.74	0.97 – 49.45	2.13 – 85.27

T tests were run to assess whether there were any statistically significant differences in travel times and distances between wave 5 (2010/11) and 6 (2012/13) of ELSA to determine how stable they were. No statistically significant differences were identified between the two waves of the data.

4.4.2.2 Does ability to walk differ by OA / RA?

One of the alternative ways of travelling would be to walk to the GP/ hospital and the majority of journeys whether walking or in the car require an element of walking (e.g. walking from the car park to the hospital). This can cause issues for instance where individuals have problems walking either from the car park to the healthcare facility, or if using public transport to or from the bus stop or interchange. As Figure 42 shows 50% of the people with OA and 44% with RA have no difficulty walking ¼ mile unaided, which means that 50% in the case of OA and 56% of those with RA do and of these 19% with OA and 25% with RA would not be able to walk ¼ mile (402 metres). ELSA asks a further question - whether participants would have difficulty walking 100 yards (91.44metres), 25% of those with OA and 29% of those with RA stated that they would have difficulty with this distance. This shows that the journey to the healthcare facilities is not just potentially challenging for those living further away, but also as a result of being able to physically access the transport system (e.g. walking to a bus stop or walking from a car park or

walking to the GP). An individual might live very close to the healthcare facilities they need to attend, but find getting to and from it very difficult.

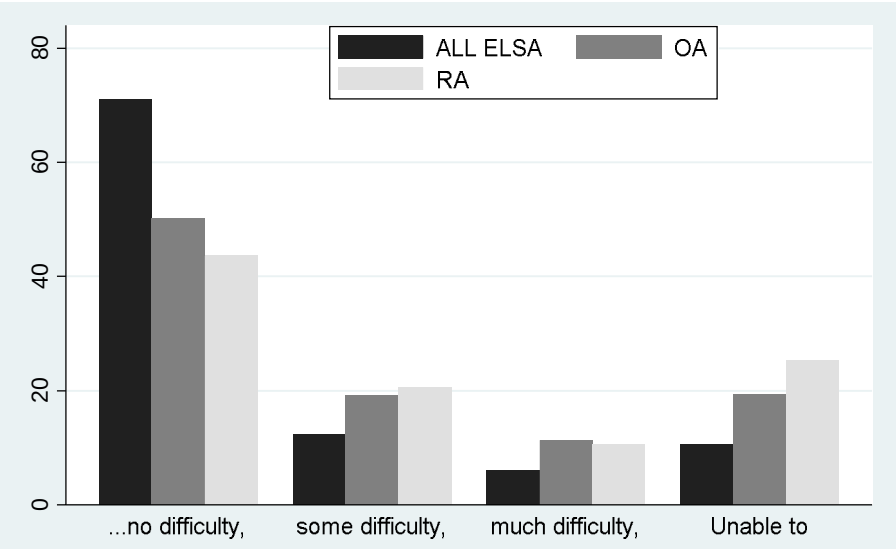


Figure 42: Comparison of ability to walk ¼ of a mile (percentages)

Using this data and distances calculated to the nearest bus stop only 1.2% of ELSA participants had bus stops within 100 metres of their homes and only 12% within 400 metres of their homes for those with RA, with similar results for the OA subgroup (1.4% and 11.4% respectively). Thus making a bus journey impossible for those who found these distances difficult. It should be noted that this was the nearest physical bus stop and did not account for whether the buses passing through this bus stop would go to where the individual might find useful or were at suitable times.

In the nurses interview in wave 6 a further indicator of mobility is provided in the form of a walk speed test. Those who are able to walk and were ≥60 years old were asked to take the test. The test measures how long it takes the individual to walk 2.44 metres (8 feet) in seconds. The average time it took individuals who had OA was 3.62 seconds, with a range of 1.1 – 46.47 (95% CI 3.50 – 3.74) compared to the RA subgroup of 3.95 seconds with a range of range 1.51 – 24.37 (95% CI 3.72 – 4.18) compared to the whole ELSA sample of 3.22 seconds, with a range of 1 – 46.47 (95% CI of 3.17 – 3.27). This translates to an average walk speed of 2.4km per hour for individuals with OA and 2.2km per hour for individuals with RA. This is a considerably slower walking speed than that used for the National Travel Survey (NTS) travel times to the GP and Hospital, which was 4.8km per hour, as discussed in Chapter 1. Using these slower walking times reduces the percentage of patients who could access the GP and or hospital within the target timeframes.

Access times to the GP and hospital will be increased if the walk speed is more than halved, or if it is assumed that individuals can't walk the 800m allowed in the NTS calculations to get to the bus stop to catch the bus. The results have shown that this is unlikely to be feasible for a large section of the ELSA population and particularly those in the RA and OA subgroups, indicating potentially less accessibility for these groups of individuals compared to the general population.

4.4.3 Using public transport

An alternative method of travel if individuals cannot travel by car is to use the public transport network. ELSA participants were asked whether they travelled by public transport and if they didn't why not. Of those who were eligible for a free bus pass (over the age of retirement) 65 % of individuals with RA and 68% of individuals with OA had got the free bus pass, which entitled them to travel for free between 09:30 and 23:00 weekdays and all day at the weekends. In total 60% of the ELSA participants with OA and 55% with RA stated that they didn't use public transport because they didn't need to. Of those people who stated that they didn't use public transport because they didn't need to 98% with RA and 97% with OA had access to a car when they needed it. The average distance to the nearest bus stop for those who said that no bus was available to them was 1 mile range (0 – 2.8miles).

In terms of health and mobility 17.4% of OA participants and 23.8% of RA participants stated that their health prevents them from using public transport. As noted above a large proportion stated that they would have difficulties walking 400 metres (1/4 mile) this is also reflected by the 16% of OA and 19% of RA ELSA participants would not use public transport due to difficulties with mobility. These two points were raised by the studies PPI group. With one member stating that these were real problems for patients with RA, whereby they didn't feel they could use a bus, as firstly, they worried about not being able to pay quick enough due to arthritis in their hands making it difficult to handle money, and then when on the bus not being able to get up quick enough when it came to their stop due to the way the disease had affect their agility and mobility.

One of the key reasons for providing those over the age of retirement with bus passes in England was to reduce the cost of travel and improve mobility. Those that stated that public transport was too expensive were not entitled to a free bus pass, which is only available over the age of retirement. There have been issues where in the past free bus passes could not be used before 09:30 on a week day (a time by which some patients have to be at the hospital by), but this was

subsequently changed to allow travel for hospital appointments for free before this time (NEXUS, 2018).

The other main options open to patients for accessing hospital healthcare (not GP) is the Patient Transport Service (PTS) run by the regional NHS Ambulance Service, which is available to book in advance. Some patients may also have access to community transport to get to healthcare appointments. The PTS takes non-emergency patients to their inpatient and outpatient hospital appointments. For example the Yorkshire Ambulance Trust undertook ~1 million non-emergency patient journeys in 2016 (NHS, 2018). Given the ability of patients to choose where they attend hospital facilities for the majority of appointment those journeys could in theory take patients living in Yorkshire to any other region in England. The ELSA survey asks whether participants have used either of these two services. Ninety-Five ELSA participants with OA stated that they used the PTS ranging from spontaneously to 2 people stating that they used it every day or nearly every day. For those with RA 4% of participants had used the PTS. Across all ELSA participants of those that used hospital transport 50% had use of a car when needed. Thus showing that there is not a clear divide between having a car and not using PTS for hospital trips.

If we assume that those who do not have access to a car or those who would be the main driver of the car have to travel for an operation such as an THR (where they would not be able to drive for 6 weeks after the operation) , they would have to use alternative methods for travelling to the hospital (e.g. either pay for a taxi, catch the bus, use the patient transport service etc…). By assuming in the models in the absence of perfect information (exactly how patients have made the journey) that everyone is travelling by car from home to hospital is likely to underestimate the travel times and in the conceptualisation of accessibility overestimate patient's accessibility to healthcare.

4.4.3.1 How easy is it to travel to the GP/ hospital?

In terms of assessing transport accessibility to healthcare, two of the key questions in the ELSA dataset are *"How easy is it to access the GP?"* and *"How easy is it to access the hospital*. How easy it is will potentially depend on a number of facets including travel time / travel distance, but also includes how easy it is for the patient to walk and the transport options available to them. The results of these questions by total ELSA population and subgroups are shown in Figure 43 for access to the GP and Figure 44 for access to the hospital. As can be seen from these histograms it is easier to get to the GP - with over 60% of the ELSA population answering that it was *very easy* to access the GP, compared to 42% stating the same for accessing the

hospital. The RA subgroup were more likely to answer that it was quite difficult, very difficult or they are unable to go compared to both the OA subgroup and full ELSA sample for both access to the GP and hospital.

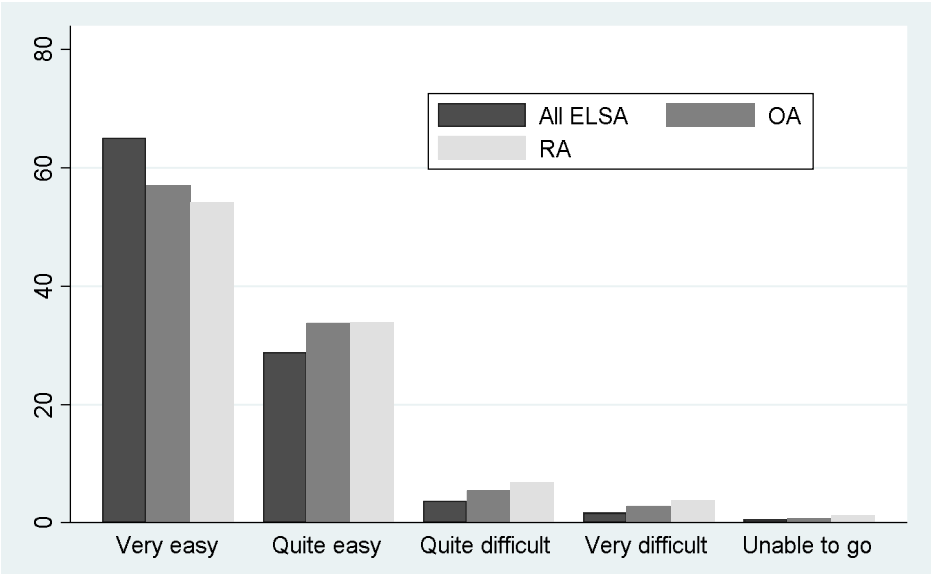


Figure 43: How easy is it to get to the GP? (Percentage of participants)

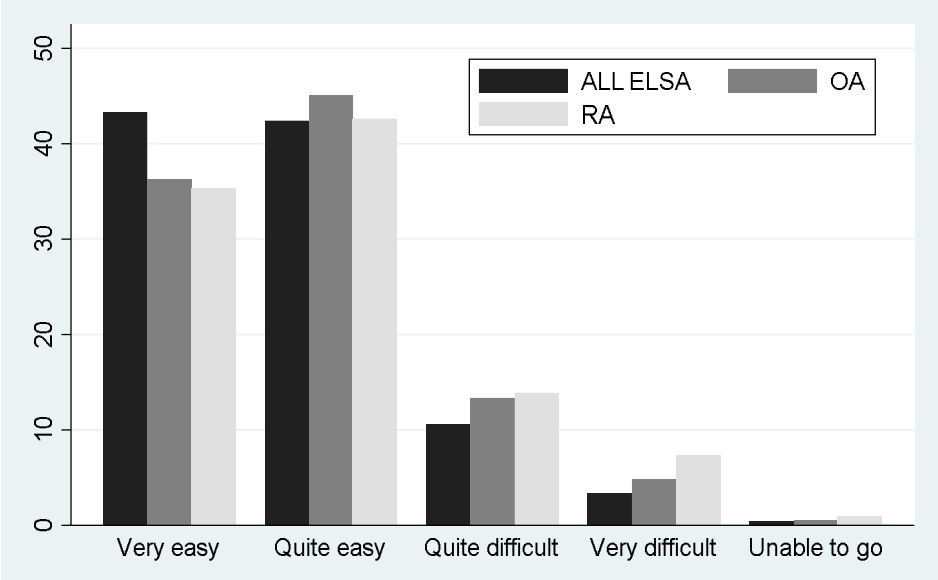


Figure 44: How easy is it to get to the Hospital? (Percentage of participants)

The study used the answers to these two questions as the dependent variable to assess whether there were any predictors of who would be more likely to a) find it difficult to get to the GP or b) find it difficult to get to the Hospital. The five categories were collapsed into 4 groups (1 = Very Easy, 2 = Quite Easy, 3 = Quite Difficult, 4 = Very Difficult or Unable to go). The categories of Very Difficult or Unable to Go were combined due to the small sample sizes. An ordered

logit model was run and the Brant test used to assess whether the parallel regression assumption was violated (different coefficients between the different categories). All of the models violated the test and so the generalized ordered logit model was used to determine the coefficients for moving between each of the 4 categories. The results of these two models are provided in Table 58 for access to the GP and Table 59 for access to the hospital. Using the generalised ordered logit model allowed those variables that had violated the Brant test (e.g. drive time, access to a car, the category of much/ unable to walk, age group 60 – 80 and comorbidities) to have differing coefficients when moving between the categories, but not all variables violated the Brant test so are represented with one coefficient that applies across all categories in the table (e.g. Ethnic group).

Starting with ease of access to the GP (Table 58) travel time in minutes violated the Brant test and so has three different coefficients. This table shows that for the full ELSA sample, as drive time (measured in minutes) increases individuals are more likely to report that they find accessing the GP less easy than would be expected (be in a higher category), so rather than Very Easy they would report quite easy and instead of Quite Easy - Quite Difficult. These results were statistically significant at the $p<0.001$ level. For the OA sub group all the coefficients were positive, but only the move between *Very Easy* and *Quite Easy* was statistically significant. This was also true for the RA sub group, with the exception of the move between Quite Difficult and *Very Difficult/ Unable to Go*, which was negative indicating that as travel time increased individuals were more likely to report that it was *Quite Difficult* compared to *Very Difficult*/ Unable to Go.

Not having access to a car was associated with participants being more likely to report finding accessing the GP less easy. This result was statistically significant for both the full sample and the OA subgroup. The strongest effect for the OA subgroup of not having a car was to make it more likely that individuals would report that it was Quite Difficult (as opposed to Quite Easy). This was also true for the RA subgroup. Individuals were more likely to report finding it less easy to access the GP if they had some problems walking.

Females were more likely to report that it was easier to access the GP than men. For the RA subgroup the model showed a statistically significant effect of females (compared to men) being more likely to report that it is Quite Difficult rather than Very Difficult / Unable to Go, so again females being more likely to report that it is easier than males. Being in the 60 – 80 age group (compared to < 60 years) was associated with being more likely to report that it was easier to access the GP, but those over the age of 80 were more likely to answer that it was less easy to access the GP. Living alone was associated with being more likely to report that it less easy to

access the GP (this was statistically significant at $p<0.05$ for the complete sample and OA sub group).

Compared to living in the least deprived quintile (1) all other quintiles were more likely to report that it was harder to access the GP, although this was only statistically significant for some of the quintiles). In terms of ethnic groups, being in the non-white British group was statistically significantly associated with being more likely to report that it was less easy to access the GP. Similarly for those with comorbidities compared with having no comorbidities. Focusing on education status and compared to having a degree or equivalent having no qualifications was associated with being more likely to find it more difficult (less easy to access the GP).

Overall a number of predictors were identified that might influence how easy it is to access the GP. The knock on effect of these are that patients might be less likely to go to the GP the more difficult they have assessed it is for them to access it, e.g. People over the age of 80, men, those without access to a car, living alone and living further away.

*Table 58: Modelling ease of access to the GP. Generalized ordered logit model. (*p<0.1,** p<0.05, ***p<0.001).*

Type (sample size)		ALL ELSA (9,335)			OA (2,166)			RA (631)		
Category		Very Easy : Quite Easy	Quite Easy: Quite Difficult	Quite Difficult : Very Difficult/ unable to go	Very Easy : Quite Easy	Quite Easy: Quite Difficult	Quite Difficult : Very Difficult/ unable to go	Very Easy : Quite Easy	Quite Easy: Quite Difficult	Quite Difficult : Very Difficult/ unable to go
Drive Time (mins)		0.07***	0.73***	0.004	0.07***	0.02	0.03	0.06**	0.04	- 0.08*
Access to a car (base = YES)	No	0.07***	0.02**	0.55***	0.75***	0.78***	0.49***	0.25	0.73**	0.33
Difficulty walking 400m (base = no difficulty	Some	0.49***	0.21**	-0.02	0.36**			0.40*		
	Much/ unable	1.32***	1.35***	1.06***	1.20***	1.44***	1.22***	1.35***		
Gender (base = male)	Female	-0.17***			- 0.11			0.05	0.03	-0.73**
Age groups (base <60)	60 – 80	-0.02	-0.46***	-0.48***	0.17	- 0.18	- 0.29	-0.23		
	> 80	0.78***	0.41***	0.40***	0.98***			0.58*	0.74**	0.16
Deprivation Quintiles (1 = least deprived)	2	0.15**			0.21*			0.37		
	3	0.16**			0.19			0.33	0.52*	-0.09
	4	0.24**			0.30**			0.40		
	5	0.23**			0.19			0.08		
Living (base = married / cohabiting	Alone	0.13**			0.23**			0.20		
Ethnic Group (base = white British)	Other	0.71***			0.75**			1.03**		
Comorbidities (base = none)	1 -2	0.12**			0.15	0.495***	0.46**	-		
	>2	0.41***			0.37*	0.50**	0.82***	0.35*	0.43*	0.82**
Education (base = degree or equivalent)	Below a degree	-0.16**			-0.07			-0.45*		
	Foreign/ other	-0.12			0.02			-0.45		
	No Qualification	0.10	0.32***	0.35***	0.30**			-0.20	0.22	0.38
	Pseudo R^2	0.098			0.131			0.1433		

The results of the models focused on *ease of access to the hospital* are presented in Table 59. The results show that the further a person lived from the nearest hospital they were more likely to report that it was harder to access the hospital. This was statistically significant for all categories. The model for the complete ELSA sample and OA subgroup violated the Brant test and has separate coefficients for moving between each of the 4 categories. As for access to a GP, not having access to a car or van when needed was statistically significantly associated with being more likely to report that it was harder to get to the hospital. Unlike for access to the GP, there did not appear to be any differences between men and women. Differing levels of deprivation did not show any statistically significant effects on the results.

Those in the age group 60 – 80 were associated with being more likely to report finding it harder to access the hospital compared to those < 60 between the categories of very easy to quite easy, but the coefficients were not statistically significant for the other categories. Those in the over 80 age group compared to the < 60 age group had a positive association with being more likely to report that it was harder to access the hospital and this was statistically significant for the complete ELSA population and OA and RA subgroups. Living alone compared to cohabiting was associated with being more likely to report being in a harder to access to hospital category. The same was the case for having no qualifications compared to having a degree or equivalent for the subgroup with OA. This was not statistically significant for the RA sub group. Being non-white British was associated with being more likely to report finding it harder to access the hospital and was statistically significant.

Overall using the generalized ordered logit model to account for the violations in the parallel assumptions resulted in the models having a higher pseudo R^2 values than for those models that assumed the coefficients were the same between all the categories indicating a better fit. When comparing between ease of access to the hospital and ease of access to the GP the key similarities were the positive associations showing individuals more likely to report that it was harder to access the hospital for increasing drive time, not having access to a car and difficulty walking, being in the over 80 age groups and not being in the white British group. Key differences included gender, where access to hospital showed no statistically significant differences between males and females, but access to the GP showed a statistically significant effect of men being more likely to report finding it harder. Deprivation showed no statistically significant association for the access to hospital models, and comorbidities had a statistically significant positive association between being more likely to report a less easy to access category to the GP categories, but a statistically insignificant association for access to the hospital.

*Table 59: Modelling ease of access to the Hospital. Generalized ordered logit model. (Legend *p<0.1,** p<0.05, ***p<0.001)*

Type (Sample Size)		ALL (7,900)			OA (2,166)			RA (520)		
Categories		Very Easy: Quite Easy	Quite Easy: Quite Difficult	Quite Difficult: Very difficult/ unable to go	Very Easy: Quite Easy	Quite Easy: Quite Difficult	Quite Difficult: Very difficult/ unable to go	Very Easy: Quite Easy	Quite Easy: Quite Difficult	Quite Difficult: Very difficult/ unable to go
Drive Time (mins)		0.03***	0.04***	0.03***	0.03***	0.02***	0.02***	0.02**		
Access to a car (base = YES	No	0.83***			0.93***			0.74**		
Difficulty walking 400m (base = no difficulty	Some	0.37***			0.38**			- 0.16		
	Much/ unable	0.79***	1.46***	1.93***	0.70***	1.36***	1.95***	0.81**	1.41***	2.14***
Gender (base = male)	Female	-0.07			0.11			0.04		
Age groups (base <60)	60 – 80	0.28***	- 0.07	- 0.20	0.29**	- 0.003	- 0.30	0.23		
	> 80	0.71***	0.32**	0.11	0.49**			0.89**		
Deprivation Quintiles (1 = least deprived)	2	0.04			0.12			-0.03		
	3	- 0.01			0.04			0.29		
	4	0.04			-0.003			0.17		
	5	- 0.01			- 0.01			- 0.31		
Living (base = married / cohabiting)	Alone	0.16**	0.43***	0.63***	0.12			- 0.04	- 0.05	- 0.05
Ethnic Group (base = white British)	Other	0.45**			0.63**			0.72		
Comorbidities (base = none)	1 -2	0.05			0.17			--		
	>2	- 0.01			0.001			0.23		
Education (base = degree or equivalent)	Below a degree	- 0.21**	-0.24**	- 0.21**	-0.25**			-0.06		
	Foreign/ other	- 0.15	-0.24*	-0.15*	- 0.08			0.04		
	No Qualification	-0.22***			- 0.07			- 0.103		
	Pseudo R^2	0.057			0.074			0.101		

4.4.4 Predicting having access to a vehicle when needed.

It was assumed in the majority of studies included in Chapter 2 that patients will have travelled to hospital or the GP by car and therefore travel time or distance using the road network would be a good marker. A UK study by Campbell et al. (2000) backed this up by undertaking a survey finding that 80% had travelled by car (a majority, but by no means all). In the ELSA dataset 82.1% of people with OA and 77.6% of people with RA stated that they had access to a car/ van when they needed it either as a driver or as a passenger, of these 63% had a car at home and could drive it. This means that there is a large proportion of individuals who do not have access to a car and this could be an underestimate of those who would have access to a car if they needed to go into hospital and did not have the option of driving home at the end their hospital episode (e.g. after having an operation). The models shown in tables 58 and 59 showed that having access to a car when needed meant that individuals were more likely to report that it was easier to access both the GP and the hospital. It would therefore be useful to be able to characterise those individuals who do not have access to a car / van when needed in order to target help in the right direction.

To identify which individual characteristics were likely predictors of not having a car / van when needed the study ran a binary Logit model (0 = no access to a car/van when needed and 1 = access to a car/van when needed), with results presented in Table 60. Individuals in the total sample were less likely to have access to a car if they are older, female, living alone or living in a more deprived residential area. Ethnic group (white vs non-white) was not found to be a predictor, but this may be due to the lack of variability (97% of the sample were White British) in the data. The OA subgroup showed the same with females, older people, living alone and the higher levels of residential deprivation, all predictors of not having access to a car. The RA sub group has the same sign on each of the coefficients, but the results were not all statistically significant (one potential explanation is the smaller sample sizes).

The results could help identify which patients might need more information on how to get to the hospital and support getting there. Equally this data could be used to assess which areas of a locality would be more likely to have individuals who do not have access to a car and is picked up again in Chapter 5 in the scenarios. Without a better understanding of how people are travelling to healthcare facilities, studies may be underestimating the true travel times and distances, as shown by the differences in travel times by public transport vs road network in Chapter 3.

Table 60: What are the predictors of not having access to a car/ van when needed?

Model : Binary Logit		Interpretation: A negative coefficient means more likely to not have access to a car.					
		No. 9336	All	No. 2,501	OA	No. 631	RA
Access to a car/ van when needed?	No Access	1,547		455		142	
	Access	9,017		2,049		491	
Gender	Male	4,729	--	856	--	237	--
	Female	5,837	- 0.37***	1,648	- 0.44**	396	- 0.31
Age groups (base <60)	< 60	3,347	--	372	--	112	--
	60 – 80	6,105	- 0.39***	1,760	- 0.84***	412	- 0.10
	>80	1,114	- 1.75***	372	- 2.11**	109	- 1.10**
Comorbidities	None	7,881	--	1,922	--	0	--
	1	2,132	- 0.496***	534	- 0.256*	441	--
	>1	553	- 0.777***	168	- 0.571**	192	- 0.497**
Living arrangements	Married/ Cohabiting	8,135	--	1,762		213	--
	Alone	2,431	- 1.69***	742	- 1.63***	420	- 1.55***
Residential Deprivation (1= least deprived quintile)	1	2,634	--	581	--	111	--
	2	2,643	- 0.40***	601	-0.18	147	-0.89**
	3	2,206	- 0.65***	538	- 0.36*	132	- 0.46
	4	1,764	- 1.21***	434	-1.13***	131	-1.06**
	5	1,310	- 1.95***	347	- 1.85***	110	-1.50***
Ethnic Group	White British	8,988	--	2,441	--	602	--
	Other	358	- 0.24	63	- 0.25	31	- 0.28
Pseudo R^2		--	0.2276	--	0.2170	--	0.188

(Legend *p<0.1 **p<0.05 ***p<0.001)

4.4.5 Measuring the association between transport accessibility to healthcare and health/ wellbeing

The previous sections of this chapter have focused on the health, wellbeing and travel abilities of the ELSA participants separately. This section now explores whether transport accessibility (measured using travel times/ distance and ease of access) is associated with differences (or inequalities) in the health and wellbeing measures (Self-Reported General Health, CASP-19, and CES_D).

4.4.5.1 Association between transport accessibility to the GP and health & wellbeing measures

As noted in Chapter 1 the GP in the first instance acts as a gatekeeper for referral for diagnosis and treatment in the case of patients with OA or RA, which may mean a referral to the hospital or in the case of RA management of treatment solely at the hospital. If transport accessibility is a barrier to preventing patients from making / attending doctors' appointments, this has the potential to have a knock on effect on individuals' health. This section of the thesis uses ELSA data to model the association between transport accessibility to the GP and health/ wellbeing outcomes. The models have expanded on the transport accessibility variables included in Chapter 3 (travel times and distances) to also include "ease of access" to the GP. Ease of access to healthcare allows a broader consideration of the factors that affect transport accessibility, as discussed in Chapter 1.

The models are firstly presented in Table 61, as an unadjusted analysis with travel times, distance and ease of access to the GP (as the independent variables) and each of the three health and wellbeing measures, as the dependent variables, by OA and RA subgroups. The tables describe the statistical model used to undertake the analysis and a description of how to interpret the coefficients. For example, a positive coefficient on the CASP-19 measure of quality of life for the continuous travel time model indicates that as travel time to the GP increases the CASP-19 score increases – quality of life increases. A negative coefficient on the Self-Reported General Health model means that an increase in travel time leads to individuals being more likely to report a better level of general health (on the scale of Excellent\Very Good, Good, Fair and Poor). The models that classify travel time/ distance into categories shows that as individuals live further away from the base line category they are more likely to have a higher score on the

CASP-19 , be less likely to have depressive symptoms (as indicated by a score ≤3) on the CES-D be more likely to self-report being in a better health category.

In summary the models with a continuous travel time as the independent variable report that as travel time increase to the nearest GP individuals are more likely to report a better level of general health, a higher CASP-19 score, and be less likely to have a score above 3 on the CES_D This is also witnessed in the categorical models, whereby ELSA participants living further from the nearest GP are more likely to have better self-reported health than those living closer.

The adjusted models are then presented separately for each health measures, which are:

- Self-Reported General Health - Table 62
- CASP-19 - Table 63
- CES_D - Table 64

The key observation from Table 61 is that it is the categorical variable – *ease of access to the GP – which* shows as a negative impact on self-reported health. Moving from reporting that it is Very Easy to access the GP to it being Quite Easy leads to an increased likelihood of reporting that self-Reported General Health is in a worse category, that the CASP-19 quality of life score is reduced (implying worse quality of life) and the likelihood of having a CES_D score of over 3 is increased (all statistically significant at the $p<0.001$ or $p< 0.05$ levels). The associations are stronger as you move towards harder to access categories. For example, for the OA model - finding it *Very Difficult or Unable To Go* to the GP compared to *Very Easy* is associated with a reduction in CASP-19 score of 13.67 (statistically significant at $p<0.001$).

This initial analysis implies that it is not as simple as reducing the travel distance / time to have a positive association with self-reported health. The results indicate that individuals living farther away are more likely to have better health than those who are closer to the GP. Ease of access might be a better measure of capturing the difficulties that people face accessing healthcare beyond the distance or travel time from A to B.

The next section focuses on each of the health and wellbeing variables separately with the adjusted analysis.

Table 61: Access to the GP - unadjusted models

	Health wellbeing measure	General Health				CASP-19				CES-D			
	Model Interpretation	Ordered Logit -ve value is an improvement				OLS -ve value is worse				Binary Logistic -ve value is an improvement			
	Sub group	No.	OA	No.	RA	No.	OA	No.	RA	No.	OA	No.	RA
Travel Time (mins)	Travel Time, mins)	2,139	- 0.05***	513	- 0.06**	2,127	0.13**	507	0.11	2,139	- 0.03**	513	- 0.05*
	R^2 (Pseudo R^2)		(0.003)		(0.002)		0.002		0.002		0.003		(0.001)
	Base = < 1 mins	238	--	52	--	235	--	52	--	238	--	52	--
	1 – 3 mins	1023	- 0.275*	259	- 0.16	1016	1.55**	259	0.35	1023	- 0.327**	259	- 0.59**
	3 – 10	750	- 0.384**	172	- 0.41	749	1.67**	172	0.97	750	- 0.341**	173	- 0.88**
	> 10	128	- 0.760***	30	- 0.91**	127	3.03**	30	1.09	128	- 0.554**	29	- 0.65
	R^2 (Pseudo R^2)		(0.003)		(0.002)		0.04		0.002	--	0.003		(0.013)
Travel Distance (miles)	Travel Distance (miles)	2,139	- 0.12***	513	- 0.14**	2127	0.28*	513	0.26	2139	- 0.07*	513	- 0.04
	R^2 (Pseudo R^2)		(0.002)		(0.002)		0.002		0.002	--	0.001		(0.001)
	Base = <1/2mile	625	--	209	--	619	--	160	--	625	--	160	--
	1/2 - 1miles	717	- 0.156	213	- 0.20	712	0.72	167	2.00**	717	- 0.20*	167	- 0.531**
	1 – 3 miles	598	- 0.252**	180	- 0.36**	598	0.95**	146	2.57**	598	- 0.20	156	- 0.719**
	> 3 miles	199	- 0.462**	44	- 0.96**	198	1.33**	40	2.74*	199	- 0.21	40	- 0.378
	R^2 (Pseudo R^2)		(0.01)		(0.006)		0.002		0.015	--	0.002		(0.015)
Ease of Access to the GP	Base = Very Easy	1225	--	276	--	1218	--	276	--	1,225	--	276	--
	Quite Easy	714	0.73***	171	0.44*	710	-4.08***	171	-3.39***	714	0.63***	171	0.44**
	Quite difficult	106	1.90***	36	1.43***	106	- 9.50***	36	-8.21***	106	1.64***	36	1.11**
	Very difficult/ unable to go	94	2.61***	30	2.39***	93	-13.67***	24	-10.97***	94	1.79 ***	24	1.36**
	R^2 (Pseudo R^2)		(0.04)		(0.03)		0.123		0.113	--	0.05		(0.034)

(Legend *P<0.1, **P<0.05, ***P<0.001)

4.4.5.2 Transport Accessibility to the nearest GP: Self-Reported General health

The results of the unadjusted general health model (Table 61) showed that living further away from the GP surgery (measured as both a continuous travel time and distance) was associated with it being more likely that the individuals would report being in a better general health category (1 = Excellent/ Very Good, 2 = Good, 3 = Fair, 4 = Poor) than those living closer, which is shown by the statistically significant negative coefficients. When split into categories of < 1, 1 – 3, 3 -10m, >10 mins of travel time it is those living the furthest away (> 10 mins) from the GP that show the strongest likelihood of reporting a better general health category. Indicating that those that live closer to the GP are more likely to report poorer self-reported general health. Using the *Ease of Access* to the GP variable there is a positive association between finding accessing the GP more difficult and a likelihood of being in a worse general health category. These results using ease of access are all positive (and statistically significant), as it becomes harder to access the GP (compared to Very Easy) the participant is more likely to report being in a worse Self-Reported General Health category.

The adjusted models for Self-Reported General Health are presented in Table 62. This adjusted the model for age, gender, ethnicity, education level, comorbidities, deprivation level, living arrangement, access to a car and walking ability. For the OA subgroup there is an association between travelling further to the GP and a decrease in the chance of reporting being in a poorer general health category (but this was not statistically significant). Indicating that those who live further away from the GP are more likely to assess themselves as being in a better general health category. As travel time to the GP increased (as a continuous variable) both the OA and RA participants were more likely to report being in a better self-reported general health category (this was only statistically significant for the RA subgroup).

Measuring travel time to the nearest GP using a dichotomous variable > 5 minutes and < 5 minutes showed that those living >5 minutes away compared to those living closer had a positive (but not statistically significant) association with having a higher likelihood of reporting being in a poorer general health category for the OA subgroup, but the opposite was true for the RA subgroup. As for the unadjusted model there was a positive and statistically significant association between increasing difficulty in ease of accessing the GP and increased likelihood of reporting being in a poorer general health category (statistically significant for both subgroups).

*Table 62: Access to the GP: the association with Self-Reported General Health using an Ordered logit model. Interpretation - negative coefficients = better general health category (Legend: *p<0.1. **p<0.05, ***p<0.001)*

				Travel time (mins)						Travel Distance (miles)				Ease of Access	
		No.		Continuous		Categorical				Continuous		Categorical			
	Sub group	OA	RA	OA	RA	OA	RA	OA	RA	OA	RA	OA	RA	OA	RA
Travel time	minutes	2,428	484	- 0.010	- 0.06**										
	Base = < 1 min)	296	52			--	--								
	1 – 3	1226	259			-0.003	- 0.149								
	3 – 10	875	172			0.057	- 0.324								
	> 10 mins	145	30			-0.267	- 0.708								
	Base = < 5 mins	2,477	497					--	--						
	≥ 5 mins	65	18					-0.156	0.188						
Travel Distance	miles	2,428	484							- 0.018	-0.116				
	Base = < 0.5 miles	763	160									--	--		
	0.5 – 1 miles	851	167									-0.059	-0.157		
	1 – 3 miles	706	146									0.025	-0.219		
	> 3 miles	222	40									0.009	-0.731*		
Ease of access	Base = Very Easy	1,294	276											--	--
	Quite Easy	767	171											0.66***	0.35**
	Quite Difficult	124	26											1.74***	1.39***
	Very difficult/unable	357	30											2.35 ***	1.92***
	Pseudo R^2			0.181	0.219	0.181	0.218	0.181	0.215	0.181	0.218	0.181	0.219	0.188	0.188
Adjusted for: Age, Gender Ethnicity, educational level, deprivation, living arrangements, comorbidities, access to a car (N/A ease of access), difficulty walking (N/A ease of access), constant															

4.4.5.3 Transport Accessibility to the GP: CASP-19

The results of the unadjusted models for the CASP-19 measure indicated that as travel distance and time increased the CASP-19 score increased indicating a better quality of life. This was only statistically significant for the OA subgroup. Focusing on the *ease of access* variable as ease of access to the GP worsened (moved away from the base of Very Easy) the CASP-19 score declined indicating a worse quality of life. This was statistically significant ($p<0.001$) for both sub groups. For example, the CASP-19 score for an individual with OA would be 9.50 lower if they reported finding accessing the GP Quite Difficult and 13.67 lower compared if they reported that it was Very Difficult or were Unable to Go compared to those who would report that it was Very Easy. This is a large decline given the scale of the measures ranges from 0 to 57.

For the adjusted models (shown in table 63) including travel time as a continuous variable was associated with a non-statistically significant improvement in the CASP-19 score. When included as a categorical variable for the OA subgroup there was a statistically significant positive association for those travelling 1- 3 minutes by car compared to those travelling less than 1 minute and those travelling greater than 10 minutes compared to less than 1 minute, but a smaller coefficient and non-statistically significant result for the category 3 – 10 minutes. For the RA group there was a negative (but not statistically significant) association between travelling 1 -3 minutes compared to 1 minute and 3 – 10 minutes compared to < 1 minute indicating a decline in score, but positive association for those travelling greater than 10 minutes compared to less than 1 minute.

For the adjusted models including distance as a continuous variable there is a positive (but non-statistically significant) association, as for the travel time with increasing distance and increasing (better) CASP-19 score. The results show that those in the OA subgroup travelling 1- 3 miles to access the GP are statistically significantly more likely to have a higher CASP-19 score than those who are travelling < 1 mile ($p<0.1$).

Using the 'ease of access' measure the results were statistically significant and showed that as the participant reported that it was more difficult to access the nearest GP the CASP-19 score declined (all statistically significant at $p<0.001$) for both the OA and RA subgroups. For example the CASP-19 score for individuals who find it Quite Difficult to access the GP would be 8.20 less than an individual who answered that it was Very Easy to access the GP.

Table 63: Access to the GP: the association with CASP-19 using an OLS model. Interpretation – positive coefficients = better quality of life

				Travel time (mins)						Travel Distance (miles)				Ease of Access	
		No.		Continuous		Categorical				Continuous		Categorical			
	Sub group	OA	RA	OA	RA	OA	RA	OA	RA	OA	RA	OA	RA	OA	RA
Travel time	minutes	2,034	484	0.005	0.108										
	Base = < 1 min)	235	52			--	--								
	1 – 3	1016	259			1.197**	-0.291								
	3 – 10	749	173			0.559	-0.401								
	> 10 mins	127	29			1.553*	1.00								
	Base = < 5 mins	1,715	425					--	--						
	≥ 5 mins	412	88					0.012	0.782						
Travel Distance	miles	2,034	484							-0.068	0.356				
	Base = < 0.5 miles	619	160									--	--		
	0.5 – 1 miles	712	167									0.351	0.513		
	1 – 3 miles	598	146									-0.015	0.892		
	> 3 miles	198	40									-0.294	2.399		
Ease of access	Base = Very Easy	1,218	276											--	--
	Quite Easy	710	171											-3.90***	-2.59**
	Quite Difficult	106	36											-8.20***	-7.16***
	Very difficult/unable	93	24											-11.89***	-7.14***
	R^2			0.239	0.288	0.239	0.288	0.239	0.287	0.239	0.289	0.239	0.291	0.273	0.299
Adjusted for: Age, Gender Ethnicity, educational level, deprivation, living arrangements, comorbidities, access to a car (N/A ease of access), difficulty walking (N/A ease of access), constant															

4.4.5.4 Transport Accessibility to the nearest GP: CES_D

The unadjusted model for the final health measure the CES-D focusing on depressive symptoms (using the < 3 and ≥3 cut offs) is presented in Table 61. The unadjusted analysis showed that an increase in travel time or distance was associated with a decline in the likelihood of a score of ≥3, so the further a patient lived from the nearest GP the less likely they were to have 'caseworthy' symptoms (score of ≥3), as defined by the cut off. Focusing on ease of access to the GP showed that those that reported that it was harder to access the GP were more likely to have 'caseworthy' symptoms.

For the adjusted model presented in Table 64 the OA subgroup recorded a small positive (but not statistically significant) association between increasing distance to the GP and increase in the chance of having 'case worthy' symptoms. When split into categories there was a mixed results over the different distances with those travelling over 1 mile having a positive (but not statistically significant) association with increased likelihood of 'caseworthy' symptoms. For the RA subgroup there was a negative and statistically significant association between travelling between 1- 3 minutes and 3 – 10 minutes compared to < 1minute and having a score of ≥3 (less likely to have 'caseworthy' symptoms). As with the unadjusted analysis finding it harder to access the GP was associated with a higher chance of being in the 'caseworthy' category.

For the OA adjusted model not having access to a car was statistically significantly associated with a higher likelihood of having "case worthy" symptoms. For the RA model there was a positive coefficient between not having access to a car and a higher likelihood of 'caseworthy' symptoms, but the association was not statistically significant. Having difficulty walking, being female, having an education below a degree, living in a more deprived location, living alone and having comorbidities were all statistically significantly associated with an increased likelihood of 'caseworthy' symptoms. Only increased age was associated with a decrease in the likelihood of 'caseworthy' symptoms.

Table 64: Access to the GP: the association with CES_D using binary logistic regression. Interpretation – positive coefficients = higher likelihood of being 'caseworthy' for depression

				Travel time (mins)						Travel Distance (miles)				Ease of Access	
		No.		Continuous		Categorical				Continuous		Categorical			
	Sub group	OA	RA	OA	RA	OA	RA	OA	RA	OA	RA	OA	RA	OA	RA
Travel time	minutes	2,501	631	0.006	- 0.022										
	Base = < 1 min)	305	78			--	--								
	1 – 3	1266	342			- 0.133	- 0.52*								
	3 – 10	900	219			0.029	- 0.66**								
	> 10 mins	153	35			- 0.058	- 0.52								
	Base = < 5 mins	2138	567					--	--						
	≥ 5 mins	486	107					0.105	- 0.109						
Travel Distance	miles	2,501	631							0.029	- 0.044				
	Base = < 0.5 miles	792	216									--	--		
	0.5 – 1 miles	876	222									- 0.115	-0.125		
	1 – 3 miles	727	188									0.117	-0.172		
	> 3 miles	229	48									0.165	-0.151		
Ease of access	Base = Very Easy	1294	298											--	--
	Quite Easy	767	187											0.588***	0.260
	Quite Difficult	124	38											1.356***	0.221
	Very difficult/unable	439	151											1.323***	0.998***
	Pseudo R^2			0.139	0.145	0.141	0.149	0140	0.144	0.140	0.144	0.141	0.145	0.106	0.160
Adjusted for: Age, Gender Ethnicity, educational level, deprivation, living arrangements, comorbidities, access to a car (N/A ease of access), difficulty walking (N/A ease of access), constant															

4.4.6 Association between transport accessibility to the Hospital and health & wellbeing measures

This section of the thesis is using the ELSA data to model the association between transport accessibility to the nearest hospital with a Rheumatology Department and health and welling variables. It considers the models for the OA and RA subgroups separately. The models are firstly presented as an unadjusted analysis with travel times, distance and ease of access to the hospital (as the independent variables) and each of the three health and wellbeing measures, as the dependent variables. The results of the access to hospital unadjusted models are presented in Table 65. The adjusted models are then presented separately under separate sections for each of the included health and wellbeing outcomes. Self-Reported general health (Table 66), CASP-19 (Table 67) and CES-D (Table 68).

The results show a negative association with self-reported general health, as travel time increases to the nearest hospital, with an increased likelihood that individuals report themselves as being in a better general health category. Reporting that it is more difficult to access the hospital is associated with a statistically significant likelihood of being in a worse general health category for both the OA and RA subgroups.

For the CASP-19 quality of life measure, as travel times to the hospital increase the CASP-19 increases (gets better) for the OA and RA subgroups. This is statistically significant for the OA subgroup but not the RA subgroup. The same association is evident for the travel distance association with individuals having a 2.43 increase in the CASP-19 score if they are living greater than 20 miles away compared to those living the closest (< 5 miles) for the OA subgroup ($p<0.001$) and 2.27 increase for those living 10 – 20 miles away for the RA subgroup ($p<0.001$). As ease of access to the hospital gets more difficult there is a larger and statistically significant association with a reduction in the CASP-19 score for both the OA and RA subgroups.

For the CES_D measure living further away from the hospital is associated with a reduced likelihood of having 'caseworthy' symptoms, but finding it harder to access the hospital is associated with a positive and statistically significant association with an increased likelihood of 'caseworthy' symptoms.

Table 65: Association between travel times and distance to the Hospital and health and wellbeing measures – unadjusted (Legend *p<0.1, **p<0.005. ***p<0.001))

	Health wellbeing measure	General Health				CASP-19				CES-D			
	Model Interpretation	Ordered Logit -ve value is an improvement				OLS -ve value is worse				Binary Logistic -ve value is an improvement			
	Sub group	No.	OA	No.	RA	No.	OA	No.	RA	No.	OA	No.	RA
Travel Time (mins)	Travel Time, mins)	2,139	-0.013***	513	-0.015**	2,127	0.067***	513	0.033	2,139	-0.016**	513	-0.003
	R^2 (Pseudo R^2)		0.0023		0.004		0.006		0.002		(0.004)		(0.0001)
	Base = <20 mines	1.667	--	397	--	1657	--	397	--	1,667	--	397	--
	>20 mins	472	-0.307**	116	- 0.428**	470	1.427**	116	2.088**	472	-0.333**	116	-0.332
	R^2 (Pseudo R^2)		(0.002)		0.004		0.004		0.009		(0.003)		(0.003)
	Base = < 10 mins	860	--	216	--	855	--	216	--	860	--	216	--
	10 - 20 mins	807	=0.122	181	0.177	802	0.999**	181	-0.385	807	-0.158	181	0.249
	20- 30	255	-0.308**	53	-0.053	253	2.008**	53	3.376**	255	-0.436**	53	-0.098
	> 30	217	-0.435**	63	- 0.603**	217	1.797**	63	0.681	217	-0.378**	63	-0.321
	R^2 (Pseudo R^2)		(0.002)		(0.006)		0.007		0.014		(0.004)		(0.006)
Travel Distance (miles)	Travel Distance (miles)	2,139	-0.160***	513	-0.147	2,127	0.873***	513	0.702	2,139	-0.172**	513	-0.120
	R^2 (Pseudo R^2)		0.002		0.002		0.007		0.005		(0.004)		(0.002)
	Base = <5 miles	1014	--	261	--	1009	--	261	--	1014	--	261	--
	5 – 10 miles	657	-0.197**	136	0.135	652	1.310**	136	0.376	657	- 0.269**	136	0.140
	10 – 20 miles	385	-0.378***	93	-0.193	383	1.685**	93	2.270**	385	- 0.315**	93	-0.349
	> 20 miles	83	-0.316	23	- 0.863**	83	2.435**	23	0.371	83	- 0.485*	23	-0.335
	R^2 (Pseudo R^2)		(0.003)		0.08		0.008		0.008		(0.004)		(0.005)
Ease of Access to the GP	Base = Very Easy	778	--	180	--	773	--	180	--	778	--	180	--
	Quite Easy	946	0.523***	214	0.012	943	-2.996***	214	-3.025**	946	0.312**	214	0.383
	Quite difficult	263	1.202***	71	0.819**	262	-6.496***	71	-7.872***	263	0.870***	71	1.296***
	Very difficult/ unable to go	122	1.931***	41	1.793***	122	- 11.345***	41	-9.933***	122	1.671***	41	1.347***
	R^2 (Pseudo R^2)		(0.029)		(0.029)		0.11		0.125		(0.034)		(0.04)

4.4.6.1 Transport Accessibility to the Hospital: Self-Reported General Health

The adjusted model for Self-Reported General Health is presented in Table 66. Travel time included in the model as a continuous variable was associated with a reduced likelihood of an individual reporting that they were in a worse health category, as travel time increased. This was statistically significant for the RA subgroup. When split into categories living greater than 30 minutes away from the hospital (compared to < 10 mins) was associated with a statistically significant reduction in the likelihood of being in a worse general health category. Indicating that living further away was not associated with poorer self-Reported General Health. Living > 20 minutes away from the nearest hospital was associated with a reduced likelihood of reporting that you were in a poorer general health category for the RA subgroup and this was statistically significant at $p<0.05$.

The RA subgroup showed a statistically significant association between increasing travel distance and being less likely to report that an individual was in a poorer health category. The OA results were not statistically significant.

The models focusing on ease of access to the hospital for both the OA and RA subgroups models showed results that as it becomes more difficult to access the hospital there is an increased likelihood of individuals reporting that they were in a worse general health category.

For the variables controlled for in the OA models not having access to a car, having difficulty walking, being male, being < 60 years old, having a qualification below that of a degree, having comorbidities and living in the most deprived 2 quintiles were associated with a an increased (and statistically significant) likelihood of reporting that they were in a worse general health category. Being female and older than 60 years old was associated with a higher likelihood of being in a better general health category.

Table 66: Access to the Hospital: the association with General Health using an ordered logit model. Interpretation - negative coefficients = better general health

				Travel time (mins)						Travel Distance (miles)				Ease of Access	
		No.		Continuous		Categorical				Continuous		Categorical			
	Sub group	OA	RA	OA	RA	OA	RA	OA	RA	OA	RA	OA	RA	OA	RA
Travel time	minutes	2,046	606	- 0.005	- 0.018**										
	Base = < 10 mins	860	280			--	--								
	10 – 20	807	228			0.095	-0.100								
	20 – 30	225	67			0.041	-0.023								
	> 30 mins	217	71			- 0.254*	-0.884**								
	Base = < 20 mins	1,667	508					--	--						
	≥ 20 mins	472	138					- 0.14	- 0.426**						
Travel Distance	miles	2,046	606							- 0.006	- 0.031**				
	Base = < 10 miles	1,014	340									--	--		
	10 – 20 miles	657	169									0.019	-0.082		
	20 – 30 miles	385	110									- 0.076	-0.320		
	> 30 miles	83	27									- 0.076	- 0.979**		
Ease of access	Base = Very Easy	778	194											--	--
	Quite Easy	946	234											0.51***	- 0.09
	Quite Difficult	263	76											1.10***	0.69**
	Very difficult/unable	122	47											1.62***	1.31**
	Pseudo R^2			0.182	0.222	0.182	0.222	0.182	0.221	0.181	0.222	0.181	0.222	0.186	0.209
Adjusted for: Age, Gender Ethnicity, educational level, deprivation, living arrangements, comorbidities, access to a car (N/A ease of access), difficulty walking (N/A ease of access), constant															

4.4.6.2 Transport Accessibility to the Hospital: CASP-19

The results of the unadjusted CASP-19 models were provided in table 62. Living further away from the nearest hospital with a rheumatology department was associated with a higher CASP-19 score (higher quality of life) for both the RA and OA groups. Whereas the *ease of access* to the hospital was associated with a decline in the score, as the ease of access was recorded as being more difficult.

The results of the adjusted models for the CASP-19 measure of quality of life are presented in Table 67. They show that there is a positive (but non-statistically significant) association with increasing travel time to the nearest hospital and very small increases in the CASP19 score. For example, an individual from the OA subgroup travelling greater than 30 minutes to the hospital would have an increase in the CASP-19 score of 0.76 compared to a similar individual taking less than 10 minutes. There were no statistically significant results for the associations between increasing travel distance to the hospital and CASP-19 score. For the variables that were controlled for – not having access to a car, having difficulty walking, having an education below a degree, having comorbidities and living in the most deprived quintiles were associated with a reduction in the CASP-19 score that was also statistically significant for the OA subgroup. Being older than 60 years old compared to < 60 years old was associated with an increase in the CASP-19 score that was also statistically significant.

Like the other health and wellbeing measures, whilst travel time or distance did not have a negative impact on this health and well-being measure the ease of access to the hospital variable did. The more difficult the participants reported that it was to access the hospital the larger to the reduction in CASP-19 score ($p<0.001$). For example, reporting that it was very difficult/ they were unable to access the hospital was associated with a reduction in CASP-19 score of 9.54 compared to reporting that it was Very Easy to access the hospital.

Table 67: Access to the Hospital: the association with CASP-19 using an OLS. Interpretation – positive coefficients = better quality of life

				Travel time (mins)						Travel Distance (miles)				Ease of Access	
		No.		Continuous		Categorical				Continuous		Categorical			
	Sub group	OA	RA	OA	RA	OA	RA	OA	RA	OA	RA	OA	RA	OA	RA
Travel time	minutes	2,034	484	0.022	0.001										
	Base = < 10 mins	855	216			--	--								
	10 – 20	802	181			0.148	0.053								
	20 – 30	253	53			0.431	2.610**								
	> 30 mins	217	63			0.762	0.148								
	Base = < 20 mins	1,657	337					--	--						
	≥ 20 mins	470	116					0.505	1.237						
Travel Distance	miles	2,034	484							0.245	0.409				
	Base = < 10 miles	1009	261									--	--		
	10 – 20 miles	652	136									0.465	0.615		
	20 – 30 miles	383	93									0.418	1.809*		
	> 30 miles	83	23									0.761	- 0.936		
Ease of access	Base = Very Easy	773	180											--	--
	Quite Easy	943	214											- 3.07***	-2.47***
	Quite Difficult	262	71											- 5.95***	-7.02***
	Very difficult/unable	122	41											- 9.54***	-5.45***
	Pseudo R^2			0.240	0.286	0.240	0.293	0.239	0.289	0.239	0.288	0.240	0.292	0.277	0.319
Adjusted for: Age, Gender Ethnicity, educational level, deprivation, living arrangements, comorbidities, access to a car (N/A ease of access), difficulty walking (N/A ease of access), constant															

4.4.6.3 Transport Accessibility to the hospital: CES_D

The final models focus on the CES_D measure of depressive symptoms. The unadjusted models focusing of access to the hospital and CES_D were presented in Table 62. For the unadjusted models living further away (in terms of travel time and distance) was associated with a reduction in the odds of being in the 'caseworthy' category. Finding it more difficult to access the hospital had the opposite association.

The adjusted CES_D models are presented in Table 68. Including travel time as a continuous variable shows a negative association with odds of having "caseworthy" symptoms, which is statistically significant for the RA subgroup (but not for the OA subgroup). As the travel time to the hospital increases the odds of having 'caseworthy' symptoms decline. When split into travel time categories those travelling > 30 mins had a statistically significant negative association with CES_D (lower odds of having case worthy symptoms). None of the travel distance models have statistically significant coefficients for the travel distance variables, but they are all negative. Indicating that those closest to the hospital have an increased likelihood of symptoms compared to those living further away.

Whilst travel distance was not found to be statistically significant, not having access to a car, having difficulty walking, being female, being younger than 60 years old, having no educational qualifications, living alone , having comorbidities and living in a more deprived residential area were associated with an increased odds of having 'caseworthy' symptoms for the OA subgroup (at a statistically significant level). For the RA sub group only being < 60 years old was associated with increased odds (at a statistically significant level) of having 'caseworthy' symptoms. Worsening ease of access to the hospital was associated with increased odds of having 'caseworthy' symptoms.

Table 68: Access to the Hospital: the association with CESD using binary logistic regression. Interpretation – positive coefficients = higher likelihood of being 'caseworthy' for depression (p<0.1, **p<0.05, ***p<0.001)*

				Travel time (mins)						Travel Distance (miles)				Ease of Access	
		No.		Continuous		Categorical				Continuous		Categorical			
	Sub group	OA	RA	OA	RA	OA	RA	OA	RA	OA	RA	OA	RA	OA	RA
Travel time	minutes	2,501	484	- 0.007	0.004										
	Base = < 10 mins	1086	216			--	--								
	10 – 20	979	181			- 0.042	0.194								
	20 – 30	304	53			- 0.107	0.077								
	> 30 mins	255	63			-0.249	-0.261								
	Base = < 20 mins	2,065	397					--	--						
	≥ 20 mins	559	116					-0.147	- 0.196						
Travel Distance	miles	2,501	484							-0.067	-0.107				
	Base = < 10 miles	1287	261									--	--		
	10 – 20 miles	790	136									-0.099	0.057		
	20 – 30 miles	454	93									-0.117	-0.309		
	> 30 miles	93	23									-0.214	-0.217		
Ease of access	Base = Very Easy	814	180											--	--
	Quite Easy	1013	214											0.296**	0.37*
	Quite Difficult	299	71											0.561**	1.22**
	Very difficult/unable	139	41											0.883***	0.85*
	Pseudo R^2			0.140	0.135	0.140	0.137	0.140	0.135	0.140	0.135	0.140	0.136	0.136	0.139
Adjusted for: Age, Gender Ethnicity, educational level, deprivation, living arrangements, comorbidities, access to a car (N/A ease of access), difficulty walking (N/A ease of access), constant															

4.4.7 Does access to the GP and hospital vary by region?

It is often noted in the literature that there is a London / outside of London divide in terms of transport availability, with London having a more comprehensive transport system allowing individuals to travel more quickly and to where they need to get to in an easier fashion than travel in other parts of the country (Institite for Public Policy Research, 2018). It is therefore important to consider the implications of comparing a centralisation policy that could be applied in London (e.g. stroke care described in Morris et al. (2014)), with a similar policy outside of London, where the distances and access to alternative transport may differ. In addition it is of interest to this thesis to make an assessment of how representative the WY case study included in Chapter 3 is of the rest of England.

Comparing across regions did show some statistically significant differences in the travel times and distances that individuals would have to travel to get to either the nearest GP or hospital. Table 69 provides a summary of the descriptive statistics for the travel times and distances and ease of access to the hospital split by the ELSA individuals in Yorkshire and Humberside (including the WY) in London and 'all others'. It can be seen that there is a statistically significant difference in the travel times and distances between these three groups, with Yorkshire and Humberside more closely aligned to the rest of the country (excluding London).

The average road network distance to a GP is 0.49 miles in London compared to Yorkshire and Humberside of 1.2 miles and all others of 1.26 miles. Table 70 shows how far away the next nearest GP would be if the nearest was closed. In terms of distance to the GP there is a 1.26 miles difference between the distance that an individual in London would have to travel to the next nearest GP and the same individual in Yorkshire and Humberside.

It is interesting to note that whilst the distances and travel times are shorter in London, a higher percentage of individuals in that region in ELSA say it is either Quite Difficult or they are Unable to get to access the GP. In terms of how easy it is to access the GP the London region individuals were more likely to state that it was harder/ unable to access the GP that the other regions. One of the consequences of having better transport infrastructure in London is a lower levels of car ownership and given access to a car is a predictor of ease of access, this might contribute to this difference that regardless of having on average closer GP surgeries it is still harder to get to a GP without a car.

Table 69: Comparing across regions (distance in miles, travel time in minutes)

		Yorkshire & Humberside	London	The rest of England
Sample size		1,107	928	8,531
GP	Straight-line distance	0.81 (SD 1.03) CI 95% 0.75 – 0.87 Range (0 – 6.51)	0.31 (SD 0.19) CI 95% 0.30 – 0.32 Range (0 – 1.32)	0.84 (SD 0.92) CI 95% 0.82 – 0.86 Range (0 – 8.49)
	Network Distance	1.20 (SD 1.39) CI 95% 1.1 – 1.3 Range (0 – 8.11)	0.49 (SD 0.32) CI 95% 0.47 – 0.51 Range (0 – 2.49)	1.26 (1.32) CI 95% 1.2 – 1.3 Range (0 – 11.86)
	Travel time	3.50 (SD 3.54) CI 95% 3.3 – 3.7 Range (0 – 25.78)	1.58 (SD 0.9) CI 95% 1.5 – 1.6 Range (0 – 9.81)	3.75 (SD 3.34) CI 95% 3.7 – 3.8 Range (0 – 25.85)
NHS hospital Rheumatology	Straight-line distance	3.70 (SD 3.04) CI 95% 3.52 – 3.88 Range (0.08 – 17.80)	1.87 (SD 0.94) CI 95% 1.81 – 1.93 Range (0.10 – 5.12)	5.55 (SD 4.54) CI 95% 5.45 – 5.64 Range (0.03 – 43.53)
	Network Distance	5.14 (SD 3.86) CI 95% 4.92 – 5.37 Range (0.17 – 28.44)	2.69 (SD 1.26) CI 95% 2.61 – 2.77 Range (0.23 – 6.89)	7.51 (SD 5.85) CI 95% 7.38 – 7.63 Range (0 – 49.28)
	Travel time	11.48 (SD 7.22) CI 95% 11.1 – 11.9 Range (0.86 – 58.69)	6.28 (SD 2.57) CI 95% 6.1 – 6.5 Range (0.92 – 17.03)	15.64 (SD 10.64) CI 95% 15.6 – 16.1 Range (0.01 - 86.18)
A & E	Straight-line distance	4.51 (SD 3.93) CI 95% 4.28 – 4.75 Range (0.09 – 19.49)	2.04 (SD 1.01) CI 95% 1.98 – 2.11 Range (0.10 – 5.12)	6.19 (SD 4.93) CI 95% 6.08 – 6.29 Range (0.10 – 43.53)
	Network Distance	6.10 (SD 4.88) CI 95% 5.8 – 6.4 Range (0.17 – 28.44)	2.97 (SD 1.36) CI 95% 2.9 – 3.1 Range (0.28 – 6.89)	8.28 (SD 6.30) CI 95% 8.1 – 8.4 Range (0.20 – 49.28)
	Travel time	13.08 (SD 14.36) CI 95% 12.6 – 13.6 Range (0.86 – 58.69)	6.86 (SD 3.39) CI 95% 6.7 – 7.0 Range(0.92 – 17.03)	17.18 (SD 11.40) CI 95% 16.9 – 17.4 Range (0.48 – 86.18)
Ease of getting to the GP	Very Easy	67.09%	63.2%	65.32%
	Quite Easy	26.67%	29.5%	28.12%
	Quite difficult/ Unable	6.24%	7.4%	6.56%
Ease of getting to the Hospital	Very Easy	44.99%	44.2%	42.93%
	Quite Easy	41.49%	43.2%	41.88%
	Quite difficult/ Unable	13.52%	12.7%	15.19%

For accessing the nearest A& E and nearest hospital with a rheumatology department the same pattern emerges, with statistically significantly different average travel distances and time in London compared to both Yorkshire and Humberside and the rest of England.

In comparison for the WY hip and knee patients the average travel time to the nearest GP was 4.26 mins and road network travel distance 1.55 miles and distance to the nearest hospital of 7.01 miles and 9.75 mins. In London using the ELSA population the nearest GP was 1.58 mins and road network travel 0.49 miles.

Table 70: If the nearest facility is closed how far away is the next nearest facility?

		Yorkshire & Humberside	London	The rest of England
GP	Network Distance	2.01 (SD 1.89) CI 95% 1.90 – 2.12 Range (0.17 – 10.81)	0.75 (SD 0.38) CI 95% 0.73 – 0.78 Range (0.10 – 2.78)	2.28 (SD 1.99) CI 95% 2.24 – 2.32 Range (0.03 – 13.79)
	Travel time	5.24 (SD 4.32) CI 95% 4.92 – 5.49 Range (0.57 – 27.63)	2.22 (SD 1.07) CI 95% 2.15 – 2.30 Range(0.36 – 11.09)	5.90 (SD 4.45) CI 95% 5.81 – 6.00 Range (0.15 – 37.74)
NHS hospital Rheumatology	Network Distance	11.05 (SD 5.99) CI 95% 10.69 – 11.40 Range (1.74 – 29.55)	4.17 (SD 1.39) CI 95% 4.08 – 4.26 Range (0.23 – 8.26)	14.73 (SD 8.40) CI 95% 14.56 – 14.91 Range (0.40 – 56.42)
	Travel time	21.70 (SD 10.38) CI 95% 21.09 – 22.31 Range (4.46 – 66.59)	8.92 (SD 2.91) CI 95% 8.74 – 9.11 Range(0.96 – 18.24)	28.23 (SD 15.02) CI 95% 27.91 – 28.55 Range (1.94 – 100.92)
A & E	Network Distance	14.47 (SD 14.47) CI 95% 13.99 – 14.95 Range (1.38 – 42.13)	4.83(SD 1.75) CI 95% 4.72 – 4.94 Range (1.17 – 11.83)	17.08 (SD 9.58) CI 95% 16.87 – 17.28 Range (1.96 – 69.15)
	Travel time	27.67 (SD 14.36) CI 95% 26.82 – 28.52 Range (4.77 – 75.45)	10.01 (SD 3.39) CI 95% 9.80 – 10.23 Range (2.43 – 25.33)	32.04 (SD 16.89) CI 95% 31.68 – 32.39 Range (5.73 – 126.12)

4.5 Discussion

This chapter has sought to use the ELSA dataset to gain a greater understanding of the potential association that having to travel to healthcare facilities has on individuals with OA and RA on health and wellbeing. Key observations that have emerged from the results are discussed next.

4.5.1 Do individuals with OA or RA differ?

The results of the analysis of the ELSA population show key differences in the sub groups that have OA and RA. The data shows that individuals with OA are more likely to be older, female, have lower levels of education, be current or ex-smokers and more likely to live alone and live in more deprived residential areas than the general ELSA population. In terms of health and wellbeing participants with OA were more likely to state that their general health was poor/ fair, have a lower level of quality of life (using the CASP-19 measure) and more likely to have a CES_D score =>3 compared to the overall ELSA population. The findings from the Arthritis calculator indicate that around 10.9% of the English population have OA in the hip of which 3.2% is classed

as severe. With a higher proportion of people with OA in the knee (at 18.2% of the population in England), of these 6.1% having severe OA in the knee.

Individuals with RA were more likely to be female, older, and live in more deprived residential areas, have a larger number of comorbidities, be current smokers than the overall ELSA population. They were also more likely to have no educational qualifications or be living alone than the general population, be more likely to live in area in the worst deprivation quintiles, be a current or ex-smokers, have no educational qualifications and be living alone than the overall ELSA population. In terms of health the results from the study show that individuals with RA have on average lower CASP-19 quality of life scores, are more likely to have a score on the CES_D above 3 and be in a poorer self-reported general health category than those with OA and the overall ELSA population. This ties in with the findings of Dominick et al. (2004)who reported that compared to individuals without arthritis "*older adults with OA and RA reported poorer general health, physical health, mental health, and sleep as well as more activity limitations and pain*" (p 5) and that individuals with RA reported lower HRQoL scores than those with OA. There are less individuals with RA, as shown by the number self-reporting in the ELSA dataset and the estimation from the Arthritis Calculator of 0.84% of the English population with RA. Individuals with RA have differing needs, on average more comorbidities and as discussed in this thesis in Chapter 1 require access to hospital when in need of treatment.

The results presented in this chapter has shown that there are key differences between individuals who have self-reported that they have OA or, RA, which will affect their demand and use of healthcare services. For example individuals with RA had on average more comorbidities. This was also evident in Chapter 3 whereby there were only 50 patients with RA who had had a THR or TKR in the WY dataset out of over 10,000 over the period 2009/10 and 2011/12, so a much smaller population affected. Data is not currently collected on PROMS from before and after starting treatment using DMARDS for RA, so the same change in health score measurement cannot be made.

4.5.2 Does transport accessibility differ?

One of the key reasons for using the ELSA dataset was that it collected a wealth of information including about how individuals travelled (e.g. Do they have access to a car?). The results showed that individuals with RA were more likely to state that it was Quite Difficult, Very Difficult or they are Unable to Go to the GP or hospital than those with OA. This was also higher for those with OA than the overall ELSA population.

The study results revealed that not having a car, living alone and living in a more deprived residential location were all associated with reporting that it was harder to access the GP or hospital. Chapter 3 used travel time or distance to the actual healthcare facility as the measure of transport accessibility. This chapter showed (particularly in Table 58 and Table 59) that travel time was an important variable in the multidimensional measure that is ease of access to the GP or hospital. These models showed that as travel time increased to the GP or hospital individuals were more likely to report being in a worse access to healthcare category. Critically these models also showed the importance of variables such as not having access to a car, or living in a more deprived residential location. These variables were independent of living further from the healthcare facilities. Two individuals living 10 minutes away from the GP, one with a car and the other not having access to a car, would have differing transport accessibility levels.

In terms of the GC model discussed in Chapter 1, we can now populate in a more complete way Figure 5, as shown below in Figure 45. We have point 0 where the individual has zero transport accessibility and is unable to travel and 1 where there are no burdens of transport accessibility. In-between there are the four categories. For the model focusing on ease of access to the GP we can see that not having access to a car, having some or much difficulty walking and living further from the GP and living on their own and having no qualifications compared to a degree moves individuals towards the left in Figure 45. This means moving from a position of it being very easy to access the GP/ hospital to being more likely to say that it is less easy to access the GP and the worst case scenario that they are unable to go.

By understanding better the weights that individuals place on burdens that restrict transport accessibility and increase GC alternative solutions can be sought. Whilst drive time has been shown to contribute to GC other aspects of GC (e.g. cost of travel, level of comfort) may play a larger part in determining an individual's transport accessibility to healthcare. For example, limited travel horizons may mean that a particular group of patients don't travel to the healthcare facilities that they need to attend. Results from Chapter 2 found that coming from a non-white British ethnic group made it more likely that that the individual would report that it is harder to access the GP and hospital (tables 52 and table 53). Previous results have identified ethnicity as an important factor, but this may be linked to language barriers for patients for whom English is a second language and/ or prior experience or knowledge of the healthcare system. Lake et al. (2011) in their study of TB treatment reported that the distance to the healthcare centre was not significant for native British patients, but was for patients who were not born in Britain.

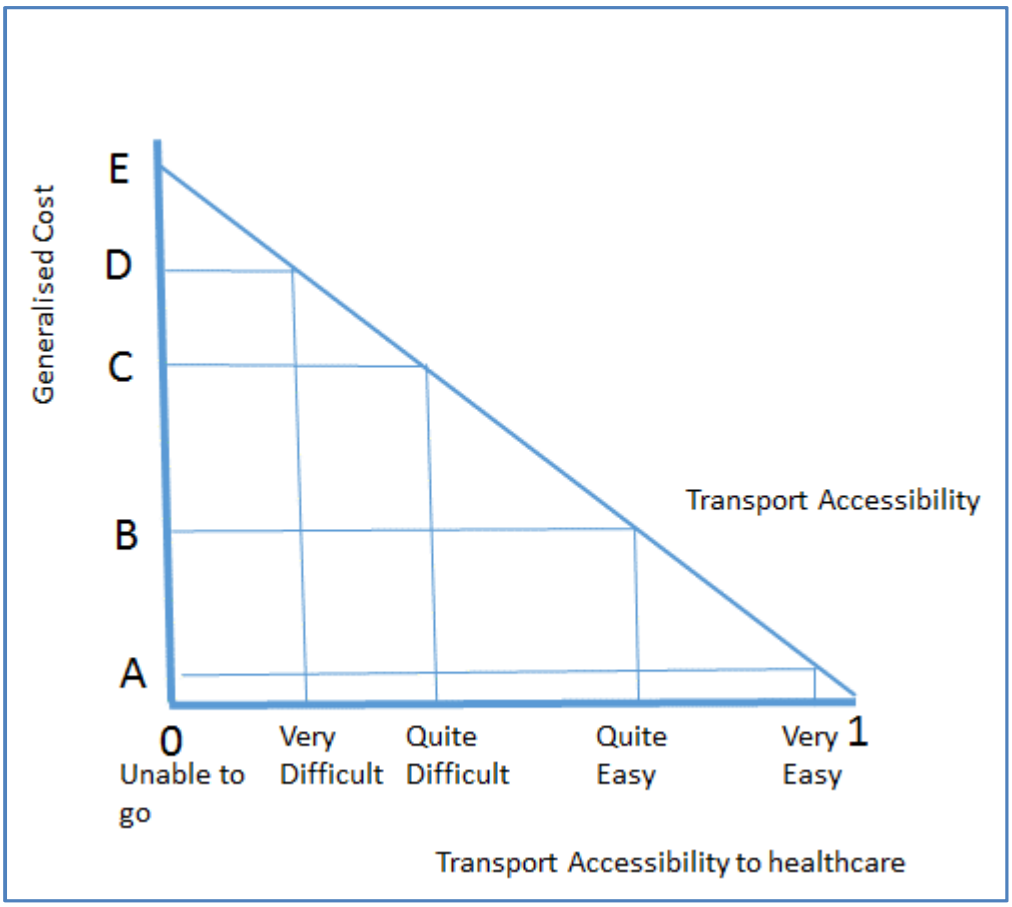


Figure 45: GC model of ease of access to healthcare

As discussed in Chapter 2 individuals may have a maximum travel time that they are willing to travel to healthcare. McGrail et al. (2015) found that communities where the population was sparsely located were found to be willing to travel a maximum of 22.2 minutes more to visit the primary care practice than those in closely settled communities. The review found evidence that patients were more willing to travel attend healthcare for critical care (e.g. Joseph and Boeckh (1981), but more likely to miss follow up appointments (e.g. Lara et al. (2005)), so different travel horizons based on the type of healthcare that was being accessed.

In a world where we do not currently have perfect information on how individuals travel and more specifically how they travel to healthcare (with the exception of those attending A & E by Ambulance) the ELSA analysis has expanded this knowledgebase. The studies reviewed in Chapter 2 and case study in Chapter 3 focused purely on a measure of travel time or distance to the healthcare facility. Using the ELSA dataset allowed a more rounded definition of the difficulties that patients face when travelling to healthcare using the definition of "how easy is it to access…" the GP or the hospital. 17.9% of those with OA and 28.9% of those with RA do not have use of a car. Of those participants with a car/ van available at home 28% of those with

RA and 20.7% with OA don't drive it. The statistically significant predictors of not having access to a car or van when needed were being female, older, living alone and living in a more residentially deprived area. The evidence showed that having access to a car when needed did not perfectly correlate with not using the NHS PTS to get to hospital, as shown by the fact that 50% of the individuals who stated that they used PTS fitted into this category. But it provides a proxy measure of a minimum of 18% of those with OA and 29% of those with RA would have to arrange an alternative method (than to use a car/ van available to them) to get to hospital. This is likely to be an underestimate of the issue, as some individuals attending hospital, particularly those having surgical procedures, will not be able to drive themselves home depending on treatment received. The SEU (2003) reported that having access to a car is only one part of the pictures with "*31 per cent of people without a car have difficulties travelling to their local hospital, compared to 17 per cent of people with a car"* (p7). Each of the statistical models found that not having access to a car was associated poorer health. This could be one of the reasons for individuals in London (with lower car ownership at around), reporting that it was more difficult to access the GP. The percentage of households without a car in 2016/17 in London was 45% compared to 24% in Yorkshire and the Humberside (DfT, 2018). The option of PTS is not available for GP appointments.

4.5.3 The GP as the gatekeeper

The research shows that the GP is the main gatekeeper in getting patients referred speedily to the hospital in the case of RA and as the main port of starting treatment and diagnosis for patients with OA. A number of the studies in the review chapter identified late stage diagnosis of cancer associated with living further from the GP (e.g. Jones et al. (2008b)). A number of potential explanatory variable were considered as factors that might be associated with individuals finding it harder to access the GP and one of these was being male. Females were more likely to record that it was easier to access the GP. The study found no statistically significant difference for how hard it was to access the hospital by gender. One of the implications of not promptly going to the GP is the potential for later stage diagnosis and further complications. For example in the case of RA not getting prompt treatment can lead to greater level of deformity, as "structural damage occurs early in active RA" (Emery et al. (2002) p290). This issue of men finding it harder to go to the GP has been considered in the literature. Banks and Baker (2013) argues that men experience barriers from two angles, firstly, getting help is seen as being "*incompatible with the masculine "norms" of strength, stoicism and self-reliance" on one side and "this reluctance makes them unwilling to overcome the many practical barriers …including lack of extended opening hours, inconveniently located services…"(*p40). This

may contribute to the findings in this study that men are more likely to report that it is more difficult to access the GP than women. Although ultimately when looking at the results for the OA and RA groups it is the women are more likely to be associated with poorer health outcomes.

4.5.4 Using ELSA health and wellbeing variables to model the association with accessibility to the nearest facilities

This chapter explored using the ELSA health and wellbeing measures (CASP-19, CES-D and General Health) the association with travel times and distances and *ease of access* to the nearest healthcare facilities. The results showed that across all models using the measure of ease of access consistently resulted in statistically significant results. As responders stated that they found it harder to access either the GP or hospital they were statistically significantly more likely to have 'caseworthy' symptoms for depression, a lower CASP-19 score and more likely to be in a worse general health category. The results using travel time or distance were mixed. With the majority showing that as travel times increased away from the healthcare facilities the health and wellbeing of the individual improved. There are potentially differences in individuals who live closer to the healthcare facilities having worse health and wellbeing than those living further away that may not have been adequately captured by the explanatory variables included in the model (e.g. BMI and smoking were not included). This will need to be explored further in future work. As discussed in Chapter 3 this could also be due to not adequately controlling for area deprivation for those living in urban areas and closer to the GP facilities. The measure of IMD is area based not individual based, so not specific to the individuals ELSA participants, but specific to the area in which they live.

Another factor could be that as in the Chapter 3 case study individuals did not all attend the nearest facility (this was not possible to ascertain from the ELSA dataset). If their actual travel times to the healthcare facilities were known and they differed because they did not attended their nearest facility, this could mean that travelling further being associated with better health outcomes is not representative , as discussed next in section 4.5.5. None of the studies in the review in Chapter 2 had applied the health and wellbeing measures, as used in this chapter. Previous studies focusing on mental health services had identified that those living further away were less likely to attend healthcare facilities (e.g. Skarvag and Wynn(2004) and MaCarthy et al (2007)).

4.5.5 Nearest vs hospital attended

This case study calculated the travel times and distances to the nearest healthcare facilities, as the actual places that the patients would attend were unknown. This mirrors a large number of

studies in the systematic review (Chapter 2), where 48% of the studies used the nearest healthcare facility as the destination point. Which measure to use nearest or actual and whether they are valid deserves some discussion, as in some cases they maybe measuring exactly the same thing and in others something very different. In order to approach this discussion I produced Figures 46 and 47, which show five patients (1- 5) and three hospitals (A, B, C). Figure 46 assumes that patients 1 -5 attend their nearest facility and Figure 47 the actual facility that they attended.

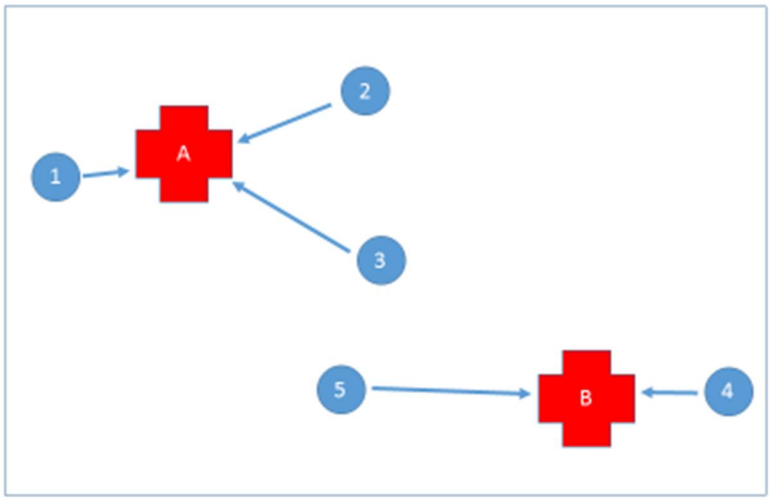


Figure 46: Nearest hospital (2 hospitals with 5 patients)

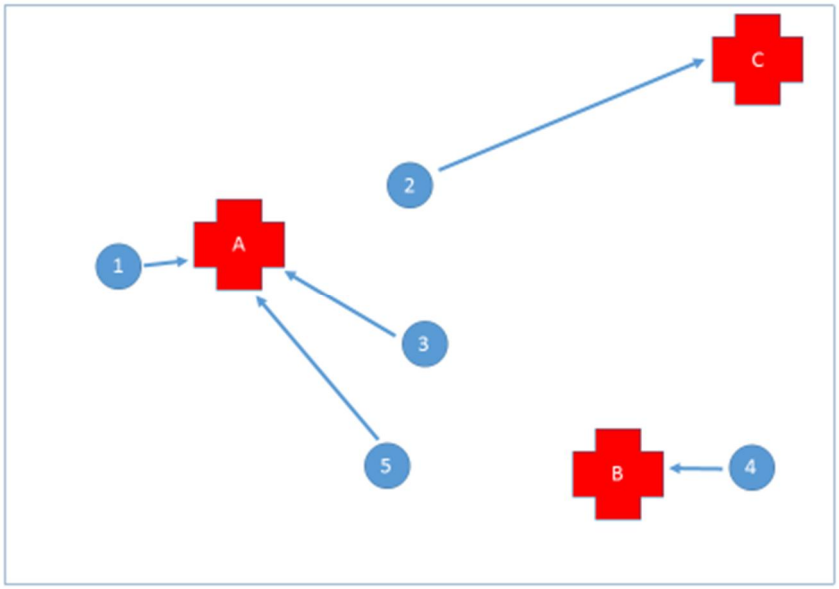


Figure 47: Hospital attended (3 hospitals 5 patients)

In this example the order of the patients is 1, 4,2,3,5 for distance from the healthcare facility for patients attending the 'nearest' facility, but 1, 4, 3, 5, 2 if considering the hospital attended.

If it could be reasonably assumed that the 'nearest' is the only option , the actual healthcare attended data is not available, there are few providers or that there are similar travel times to alternative options then using the 'nearest' would be a good approximation for the actual hospital attended. Whilst in the context of THR and TKR and access to healthcare for patients with OA and RA there are currently multiple providers and choice over where to attend. There are other examples in healthcare where the nearest is more likely to be the actual hospital attended. Since 2009 patients have had the right due to changes in the NHS constitution to choose where they want to attend for their first outpatient appointment for elective surgery (e.g. for THR or TKR) and their GP surgery, There are however other diseases and treatments where there is no choice for patients over where they can be sent, for example: emergency services, rapid access pain clinics, some cancer services maternal health and mental health services (NHS, 2019a), under these scenarios the actual centre that treats patients for these diseases is more likely to be the same as the 'nearest facility'. Although not always, as there are examples where due to a lack of beds patients are sent out of their local area, with examples in maternity(Merrick, 2018) and mental health treatment(Campbell, 2018).

One of the issues with using the nearest facility that can be deduced from Figure 46 and 47 is that some patients that are closer to the nearest facility may have actually travelled the furthest to the hospital attended, as shown by patient 2 in Figure 46 and 47. As noted in Chapter one of the patients in the HES-PROMS dataset who travelled the furthest from their home postcode to the hospital attended when assuming that they attended their nearest hospital had one of the fastest travel times (so was closest). Using the nearest in the case of patient 2 and the patient in Chapter 3 will reduce the travel time associated with the health outcome that is included in the model, so would not be measuring the association that travelling further to the facilities had on their health outcomes. It will also change the ordering of patients in terms of travel time/ distance to the hospital included in the model. One of the key reasons why patients have attended a wide range of hospitals (31) for TKR and THR is that they have choice over where to attend and there are many hospitals within a short additional travel time, so there is more scope for the nearest not to be the actual hospital attended. This is shown by the WY case study where only 36% of the patients attended their nearest hospital for their THR or TKR. This is similar to the results found by Tracey et al. (2014) where 38% of women attended the nearest facility for treatment for ovarian cancer. In both of these cases applying the nearest facility approach means that over 60% of the patients in each case would have been allocated to a hospital in the travel time calculations that they did not attend, so could be a very different travel time than the one they experienced.

Another argument for using the nearest facility is for scenarios where it could be assumed that if patients did bypass their local hospital then this is in itself an indicator that they have better levels of transport accessibility in terms of being willing and able to travel further. This is also one of the arguments put forward for the studies that showed a bias towards living further away and having an improvement in health outcomes, where patients living further away were argued to be healthier and more motivated to travel to the specialised centres (Lipe et al., 2012), so maybe less affected by the increase in travel time that this decision have resulted in, so less affected by ease of access issues. However, choice of healthcare facility is likely to rely on a number of different factors other than ease of access e.g. GP recommendation or GP preferred provider, reputation, ease of access for visitors and the 'nearest facility by travel time' might not have featured in this choice. For example, one of the members of the PPI group stated that - they had chosen a hospital based on how easy it was for their family to travel to the hospital by bus rather than selecting the nearest hospital (by car) that they would have attended. This could be shown in the Figures 46 and 47 by patient 5 attending hospital A, which was in fact easier for their family to get to by public transport than the 'nearest' hospital B. Another example was given where, one of the PPI group described that they were advised by their doctor to attend a specific hospital and be seen by a specific consultant for treatment for RA, which bypassed their local hospital. This resulted in an extra 12 miles to get to the appointments and extra 30 minutes of travel time compared to the nearest appointment. This was not on the basis of finding it easy to travel to (as the individual had to use the PTS to get to the hospital), but that the choice of hospital was made and the travel arrangement had to follow on after. This can be shown in Figures 46 and 47 by an assumption that person 2 has travelled to hospital A, as their nearest, but has in fact been sent by their GP to Hospital C. By assuming this person is attending the nearest facility rather than the one that was attended could, it might be argued misrepresent their transport accessibility and association of this (especially as they were making multiple trips) with their health. Using the travel time categories in Chapter 3 and 4 and assuming that they had attended their nearest this would put them in the base group in the models (< 10 mins), where a more representative travel time that they experienced would be the > 30 minutes group. Assuming that patients have attended the 'nearest' facility may have the undesirable impact of reordering the patients in terms of who have actually travelled the furthest (if we want to know the impact of travel time (as a proxy for transport accessibility) on health outcomes and distorting the data.

There are likely to be patients for which a longer distance or travel time (and subsequent impact on GC) would not have a large effect on their levels of transport accessibility (due to being fairly inelastic in demand). This could be one of the possible explanations for the distance bias results

in Chapter 2, whereby patients travelling further for their treatment were shown to have improvements in health compared to those who travelled a shorter distance – the impact of increasing the distance/ travel time does not impact on their transport accessibility. Equally assuming that those living nearest the 'actual' or 'nearest' hospital have better transport accessibility (in the context of the broader range of factors discussed in Chapter 1 and GC formula) maybe a gross simplification and may go some way to providing one potential explanation for why in the some of the studies those living closest to the healthcare facility maybe associated with worse health outcomes (i.e. it is not just the pure distance or travel time from A to B by car). So patient 1 travelling to hospital A whilst having a shorter distance, may find it harder to get to the healthcare facility than patient 5.

4.5.6 Do travel times to the GP or hospital differ by region?

The study wanted to know how different the travel times and distances to healthcare facilities were across the different regions in England. This was in order to, firstly, make an assessment of how different the travel times used in Chapter 3 (WY case study) were compared to the rest of the country and secondly, how different the scenarios would be centralising healthcare in London compared to the rest of the country. The results showed a statistically significant difference in the travel times to the GP and hospital in Yorkshire and Humberside compared to London, with London having on average quicker travel times to the nearest GP, hospital and A & E. The travel times in Yorkshire were more similar (but lower) to the 'rest of the country'. Interestingly, whilst the average travel times to a GP in London were statistically significantly shorter than the rest of England a higher percentage of individuals in London (7.4%) reported that it was quite difficult or they were unable to go compared to the rest of the country. This also plays into the above discussion whereby transport accessibility to healthcare is not simply the travel time to the facility - it is more complex than that. The results indicate that London has very differing results to the rest of England, but that Yorkshire and Humberside has comparable travel time / distance (if slightly faster) than the rest of England (excluding London). This was also true for the results that focused on where the individual would have to travel to attend the next nearest facility if the closest were shut. This could partly be explained by the less densely populated areas outside of London, but also through research that has shown that some areas of the UK have in the past had less access to healthcare facilities than others. This issue was first identified by Tudor Hart (1971) who wrote about the inverse care law where he concluded that *"in areas with the most sickness and death, general practitioners have more work, larger lists, less hospital support and inherently more clinically ineffective traditions of consultations, than in the healthiest areas and hospital doctors shoulder heavier caseloads with*

less staff" (p412), so exacerbating health inequalities across the country. This inverse care law highlighted that good quality healthcare was inversely associated with the need for it in the local population. This trend of some areas across the UK having fewer GPs for the need of the population they are serving still holds. Data has shown that there is a Forty percent variation in GPs per patient across the Regions in England, with South London and the South West NHS regions having the highest number of GPs per patient and the East midlands the lowest number of GPs per patient (NHS Digital, 2018b),so a variation.

4.5.7 Limitations

The ELSA case study has allowed the thesis to explore a wide range of factors that can affect an individual's transport accessibility to healthcare and has been able to focus on three self-reported measures of quality of life (CASP- 19), general health and levels of depressive symptoms in the ELSA population. However it does have a number of limitations. Firstly, there was no data available on the healthcare facilities that patients had attended or if they had even attended a healthcare facility (GP or Hospital) in the timeframe of the survey. As noted before, this part of the study was designed to use the linked HES –ELSA dataset, which would have not only given more information on whether they attended healthcare facilities in the time period, but where they attended and how frequently. This limited the analysis to assuming that any healthcare facilities that they had attended were the nearest facilities to their home address. Critically having the linked HES-ELSA dataset would also have allowed an assessment of self-reported diagnosis vs. clinical diagnosis of OA and RA by comparing the diagnosis codes in HES with the self-reported diagnosis in the ELSA survey. As discussed in Chapter 3 there is a wide variation in the case of patients with radiographic evidence of OA not having a symptomatic diagnosis of OA and vice versa and some patients with a diagnosis not realising that they have a diagnosis (Parsons et al., 2015). For example, were there some individuals in the ELSA dataset that had not correctly answered whether they had either OA or RA? As discussed in Chapter 1 and 3 there are different ways that OA and RA can affect an individual (e.g. different joints affected), this was not possible to pick this up using this secondary dataset.

The study has highlighted the association between 'ease of access' and worse health outcomes. It would then have benefited from some qualitative research to explore in more depth how individuals interpret this measure aside from the interpretation of the data in this chapter. This was highlighted by the PPI group, who in the discussions were able to provide some suggestions in terms of factors that helped their ease of access.

One of the limitation of the application of this dataset in this thesis is that it is used as cross sectional data (rather than making use of the panel data). It was only possible to get the grid link references for waves 5 and 6 at the time of the study and only wave 6 included the nurse collected health data. Future work could improve the analysis by making use of the panel data, which has the potential to see whether changes in health (e.g. depressive symptoms) over a time period were associated with being closer or further away from the healthcare facilities and whether they fluctuated. It would be possible to update this work with future waves of the data to explore whether the associations change over time.

4.6 Conclusions

This Chapter has applied the ELSA dataset health and wellbeing measures to analyse the association between travel times, distances and ease of access to the nearest GP and hospital for individuals with OA and RA. One of the main findings has been that including travel times ad distances as the proxy measure of transport accessibility may underrepresent how easy or hard it is for individuals to travel to the hospital or GP. Whilst *ease of access* to the GP and hospital was found to be statistically significantly associated with poorer health and wellbeing in terms of Self-Reported General Health, CASP-19 quality of life measure, CES_D measure of depressive symptoms, living further away (by distance or travel time) from the hospital or GP was associated with better health and wellbeing, but was statistically significantly associated with poorer ease of access. There is a large degree of variability in access to the GP and hospitals across England. Interestingly, although having the shortest drive time and distance to the GP, those ELSA participants living in London had a higher percentage of individuals who stated that it was very difficult or were unable to go, implying that the issue is not as simple as focusing on travel time and distance. The travel burden for different individuals (e.g. with and without a car) will be different.

The key findings that will be taken forward to Chapter 5 are:

1. Given that the results show that not having access to a car when needed is associated with poorer health and wellbeing outcomes, not knowing how individuals are travelling in the national datasets seems a missed opportunity to tackle some of the potential health inequalities. Using the predictors of not having a car presented in this chapter (gender, age group, living arrangements, comorbidities, residential deprivation and ethnic group), which are also present in the WY dataset it would be possible to estimate, which of the WY patients is likely to have access to a car and use these in the scenarios in Chapter 5.

2. There is more confidence in the generalisability of the WY case study given the comparison of distances/ travel times across the regions in England (excluding London).
3. Increasing travel time as part of the *ease of access* measure is associated with poorer health and wellbeing. The requirement for particular groups of individuals to travel further to the GP or hospital could lead to a worse association with health and wellbeing.

Chapter 5 will use the WY case study described in Chapter 3 and undertake a number of scenarios changing where the THR and TKR patients would access the hospital. For each of the scenarios an assessment is made on which individuals would be negatively or positively affected by the change and assesses what is the impact on health outcomes. It then estimates using the predictors of not having a car, which of the WY patients could be expected to not have a car. The scenarios are then re-run focusing on this subgroup.

5 Chapter 5: Policy – Modelling changes to the provision of healthcare facilities

5.1 Introduction

Chapter 2 reviewed the evidence on travelling further to healthcare facilities and associations with health outcomes. Chapters 3 and 4 undertook detailed case studies at a local level (WY) and national level (England) to focus on differences in health and wellbeing associated with differences in distance or travel time to healthcare facilities. Up to this point there had been no consideration of what a policy of reconfiguring of where patients access the healthcare system might look like and the impact this might have on patients travel times to healthcare facilities. Chapter 5 is designed to develop and test a number of potential changes (scenarios) to where patients access healthcare facilities. The analysis to date, and other published work, have documented the inequalities in the geographical distribution of both GP practices and hospitals in England, (e.g. Gravelle and Sutton (2001)). Changing this further through a process of reconfiguration has the potential to widen these geographical differences, and potentially increase health inequalities.

Since April 2008 patients in England have been able to choose any hospital across England (that takes NHS patients) for the majority of NHS treatments (exceptions include emergency services, cancer services, maternity services and mental health services). As shown in Chapter 3 only 36% of patients attended their nearest hospital for their THR or TKR with 64% travelling further. A policy such as centralisation of services that in effect restricts choice could have the impact of reducing rather than increasing the average travel times that some patients would have chosen to travel, but still increase travel for others. It is worth noting as shown by the results in Chapter 4 that *ease of access* to the hospital or GP is not just about travel time or distance alone. It could be possible to reduce travel times by car, but at the same time make the healthcare facilities less easy to access by other forms of transport.

5.1.1 The policy of reconfiguring and centralising healthcare services

Reconfiguration of healthcare services is "*a deliberately induced change of some significance in the distribution of medical, surgical, diagnostic and ancillary specialties that are available in each hospital or other secondary or tertiary acute care unit in locality, region or health care administrative area"* Fulop et al. (2012) (p128). Centralisation is one possible reconfiguration, whereby patients are treated in a smaller number of specialising hospitals. The drivers for

promoting changes to how the healthcare services are provided tend to be due to one or more of the following reasons; cost, quality of care, access to healthcare facilities and workforce issues. The majority of studies in the literature have focused on the first two of these.

Costs have been a key driver for changing how services are provided. The King's Fund (2018) summarized the current state of the NHS in England by highlighting that in 2017/18 that 44% of Trusts were in deficit and that total deficit for 2017/18 was £960million. Reconfigurations that aim to save money are in part therefore to try to meet demand whilst coping with increasing costs. Palmer (2011) argues that where there are limits to efficiencies that can be implemented in hospitals "more significant productivity improvements requires redesigning the way patients flow into, through and out of hospitals, in order to allow reductions in hospital capacity and to make savings" (p7). There is the potential to change how one hospital caters for the patient care pathway or change which treatments are provided across a number of available hospitals. There is mixed evidence as to whether reconfiguring healthcare services can achieve cost effective savings. For example, Hollingworth and Ness (2012) reviewed 20 studies that had evaluated whether centralisation of cancer care was cost effective (the health gains represented value for money), finding that 68% of the included studies showed evidence of cost reductions, but only one study was able to provide evidence that it had been cost effective.

In terms of quality of care a growing body of literature explores whether there have been any improvements in health outcomes as a result of reconfiguration of where patients attend / are sent. For example, (Morris et al., 2014; Woo et al., 2012; Forshaw et al., 2006) all found evidence of improved health outcomes where patients were treated at specialised centres. Morris et al., (2014) and the updated Morris et al. (2019) focused on evaluating the impacts of centralising stroke care in London and Manchester. Prior to centralisation patients with a suspected stroke in the Greater Manchester area were sent to one of 12 hospital; after centralisation patients were sent to one of three hospitals that were hyperacute stroke care centres (one open 24/7 and two open between 7am and 11pm). In London prior to centralisation there were 30 hospitals for stroke admission , after centralisation patients would be sent to one of 8 hyperacute stroke care specialised centres. Results published from this study have found that this has been associated with reduced mortality rates and LoS in acute hospitals. However, there was no evaluation of the impact on travel times – patients would be sent to the nearest hospital at the time.

Reconfiguration has also been argued as one solution to cope with increasing demands for healthcare services whilst restrictions have been placed on the number of hours the workforce can work and the availability in the NHS for senior staff to be based across multiple sites all

covering the same specialisims. The introduction of the European working time directive (applied to doctors from 1st April 2004) restricted the number of hours of work to no more than 48 hours a week (EU, 2004), which put a strain on maintaining appropriate staffing levels, which were reliant on junior doctors completing more than 48 hours per week. This combined with shotages of healthcare staff has meant that trusts often struggle to maintain adequate staffing levels across the NHS. A thinktank piece by The Kings Fund has forecast that unless change happens "NHS staff shortages could reach 250,000 by 2030"(Iacobucci, 2018) (p9). Workforce pressures are likely to be one of the most significant drivers of reconfiguration, as moving care for specific treatment to smaller numbers of sites requires for example less volume of specialist staff to oversee the running of the services resulting in potential economies of scale.

The final driver, and the focus of this thesis, is access to healthcare facilities. Indeed good access is not just about getting an appointment when patients need it. It is also about access to the right person, providing the right care, in the right place at the right time. There is a need to provide services in the right place to meet patients' needs. Research by Basemap (2015) used GIS methods to calculate travel times for patients to stroke care if one of two hospitals were shut in Somerset, UK. The conclusion was to keep both hospitals open, as the additional travel time for some patients could adversely impact on the speed by which they are treated (and knock on impacts on health outcomes). Stroke care is interesting because treatment and outcomes are very time dependent – the quicker you are treated the better the outcome is likely to be. Whilst elective surgery such as THR and TKR is not as time dependent. Changes to where services are located as a results of policies such as centralisation or reconfiguring where operations take place may still have a big impact – especially for those individuals who do not have access to a car to make the journey and instead rely on public transport or other services including the PTS to get to appointments (Lovett et al. (2002)).

Service reconfiguration changing where patients attend hospital is not a new policy in the UK. There is a process in place where health authorities want to make changes. Following the NHS (2006) National Services Health Act 2006 health authorities are required to put out any significant service change to a public consultation and any proposed changes must be assessed against four tests, which are known as the Lansley (after the then secretary of state). These four tests are described *in Barratt and Raine (2012) and summarized* below :

- Does the proposal have support from GP commissioners?
- Has there been strengthened public and patient engagement?
- Is there clarity on the clinical evidence base?
- Do the proposals provide consistency with current and prospective patient choice? *(p20)*

Whilst these tests have been set up by the NHS, it is expected that health authorities will apply them in their local situation. In England there is an Independent configuration Panel (ICP) that is set up to review proposals for changes to NHS services, but also significant reconfiguration changes. On their website they list that in the last year they have provided "advice on referrals from West Yorkshire, Northumberland and South Tyneside and Sunderland" for reconfiguration of services (Independent Reconfiguration Panel, 2019).

Current policy requires that local areas in England (e.g. WY and Harrogate) produce Sustainable Transformation Plan (STPS) to document how they will provide care in their local area now and in the future. The WY and Harrogate Plan has a key aim of reducing health inequalities in the area (NHS England, 2018b). Other areas in England have proposed changes to service provision in their STPs including, merging hospitals (e.g. Royal Bournemouth and Poole Hospital in Dorset), proposing shutting some A & E departments and downgrading the types of patients that they can treat (e.g. Dewsbury), closing maternity units (e.g.Alston, Maryport and Wigston in Cumbria) and shutting or downgrading acute hospitals (e.g. keeping one out of three acute hospitals in Leicestershire open) (BBC, 2017).

In WY, whilst there is no current plans for reconfiguring the hospitals providing THR and TKR there is a precedence for reconfiguring stroke care. Before 2007 healthcare providers in each of the NHS trusts within West Yorkshire and Harrogate moved to select one hospital (where there were previous multiple sites providing stroke care) to centralise care resulting in five hospitals that would provide Hyper Acute Stroke Units (HASU). The hospitals were Leeds General Infirmary (LGI), Harrogate District Hospital, Calderdale General Hospital, Pinderfields Hospital and Bradford Royal Infirmary. Sites were selected based on workforce issues, efficiency arguments and evidence from the London case study that sites that see less than 600 cases in a year have worse health outcomes (mortality and LoS). A subsequent review had identified that two of the sites do not currently achieve 600 cases a year (Harrogate District Hospital and Pinderfields Hospital) and the hospital that takes the largest number of stroke patients (LGI) does not exceed what had been determined as the upper limit before a provider gets too big to achieve health benefits of 1,500 patients per year (NHS England, 2015). A new consultation reviewing the current situation and considering the future is focusing on limiting these hospitals to 3 or 4 rather than 5 in the future in part based on meeting the quantity targets (Networks, 2016).

In terms of orthopaedics there are examples across hospitals of plans to reconfiguring elective surgery on one site. For example, Heart of England Foundation Trust (2014) included proposals to locate elective surgery for orthopaedics at one hospital rather than carrying out the procedure at three hospitals to improve efficiency and tackle workforce issues.

Rather than reconfiguring services across existing hospital providers an alternative option would be to build a new hospital to meet demands. There are signs that this is one of the focuses of the current UK Government. For example, in 2018 it was reported in the press that the Government would aim to build one new hospital a year (Smyth C, 2018) There are a number of new hospitals currently being built in the NHS. For example, there are two new hospital buildings planned in Leeds (within the WY case study) (Trust, 2019). The NHS has produced guidelines for building new hospitals (DH, 2014), where it is clear that the plan needs to provide "access and easy circulation for patients, staff and visitors (both non-disabled and disabled) on foot, on bicycles, in cars or on public transport (sustainable transport considerations should be encapsulated in a transport plan);dedicated blue light routes and a discrete segregated access for goods vehicles to receiving and delivery areas" (p16). They also highlight the need to consider parking areas and locating hospitals within good public transport routes.

One of the ex-panel members on the ICP in his review of the reconfiguration process within the NHS challenged the NHS "to build greater consideration of accessibility issues into its reconfiguration proposals" (p8), as he argues that whilst access is considered as one of the drivers of reconfiguration it is usually seen as "just something that has to be accommodated within proposal"(Barret, 2012)(p5). More work therefore needs to consider the impact on patients. Implementing policies including centralisation or reconfiguring where services are located within an area requires a big step change in current practice, as shown by the four Lansley criteria. Drawing from the results of Chapters 2 – 4 it is evident that travel to healthcare could play a role in patient health and wellbeing and therefore any changes to where patients attend healthcare should be evaluated accordingly in terms of access, alongside the other key drivers of quality, cost and workforce pressures.

With a growing body of literature showing an association between higher volume providers of THR /TKR having better health outcomes(Hervey et al., 2003; Katz et al., 2001) and higher volume surgeons having better health outcomes (Ravi et al., 2014; Basques et al., 2016) in terms of shorter LoS, less post-operative complications and lower mortality rates. Considering to reconfigure where patients access healthcare services is a valid approach for this patient group. This chapter considers a number of different options or scenarios based on similar changes proposed or made as a result of reconfiguration to services in the NHS.

5.1.2 Operationalising the reconfiguration/ centralisation

Operationalising the process of investigating changing where healthcare services should/ could be located can be tackled in a number of different ways. A scenario requiring patients to attend

their nearest hospital, could be completed in a similar way to the case studies in Chapter 3 and 4, whereby the distance/ travel times to the nearest facilities are calculated (essentially not giving patients a choice and minimising their travel). Following this policies such as finding the one central location that minimises the travel times/ distance (likely to be a central major city hospital) become more complex requiring GIS software. After this the options become more complex, requiring models that optimise the number of hospitals attended (e.g. location-allocation models - see section 5.2.2) and making changes to minimise the impact on accessibility levels through assessing the impact of closing specified hospitals on travel time thresholds. A number of potential scenarios are presented in this chapter ranging from attending the nearest facility to minimising the number of hospitals that could be attended to allow an assessment of potential associations with health outcomes

5.1.3 Access to a car

One of the major limitations of the HES-PROMS WY dataset used in Chapter 3 was that data had not been collected on how patients travelled to hospital for their appointments. Results from Chapter 4 identified that among other characteristics not having access to a car was associated with poorer health and wellbeing. Chapter 3 also identified mirroring those results of Kim et al. (2000), that there was a negative association with those living the closest and those living the furthest away (a U shaped distribution). This ties in with the concept that it is not necessarily the distance or travel time that is the issue, but the ease of access associated with travelling to the hospital or GP (of which distance however long or short contributes). The journey for a patient living 30 minutes away from a GP, who can travel by car directly from home to the GP, and park close by minimising walking distance, is likely to have less of an issues travelling to healthcare compared to a patient living 800m from the GP, without access to a car and with a reduced ability to walk. If the process of restructuring could be weighted to reduce the impact of travel to healthcare on the group of individuals who find it harder to access healthcare (noting that for some the increased distance does not impact on their health) then this could contribute to reducing health inequalities. To focus on this issue section 5.4 estimates using the missing data methodology applied in Chapter 3, which of the WY patients are more likely to not have access to a car.

The next section of Chapter 5 starts by describing the data and methods that are being used to develop and test the different policy scenarios. It then tests a number of different scenarios and summarises their differences. Missing data methodology is used to estimate which of the WY patient population is more likely to not have access to a car (Section 5.4). The scenarios are then run again to see whether there are any differences in the results if the policy is focused on those

who are less likely to have a car. Section 5.6 focuses on whether it matters how patients travel, which is then followed by discussions and conclusions.

This chapter targets objective 4, of the study, which is:

- *To test the results of the systematic review and statistical models to explore policy implications of restructuring healthcare services for individuals*

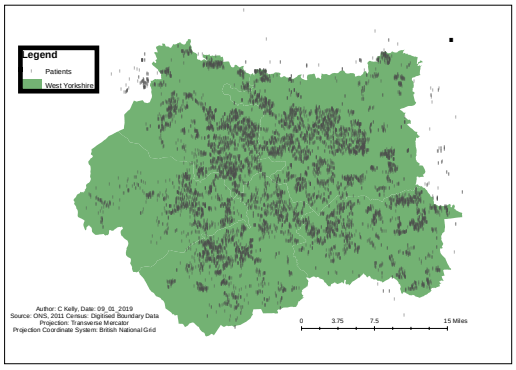
5.2 Data and methodology

5.2.1 Data Description (patient vs population data)

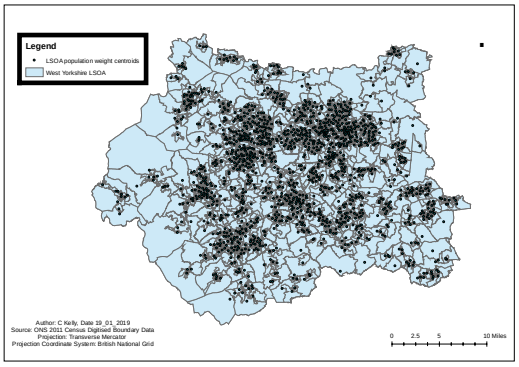
The analysis uses two populations to develop and test a number of reconfiguration scenarios, which are the WY HES-PROMS THR and TKR patient data included in Chapter 3 and the WY population data, which is represented by the LSOA zones in WY. There were 10,875 patients (see Map *4*) in the patient population and 1388 LSOA zones in the WY population (see Map 5). Within each LSOA in England there are on average 1,614 people (ONS, 2017). This provides a WY THR/TKR patients vs WY population approach. The LSOA were created by ONS to improve the reporting of small area statistics. They included large enough numbers of people so that it was less likely to be able to identify individual people from the data. The study has used the population weighted centroid of the LSOA to compare with the patient data as the starting location. This is the median centre point of all people living in the LSOA. For an LSOA covering a wider geographical area there is the potential for people to be living some distance from the LSOA population weighted centroid. For others in densely populated urban areas it is likely to be a more accurate representation of where they actually live. As shown already in Chapter 3 there was no statistically significant difference in the travel times when comparing the LSOA and the home postcode as the starting points for patients travelling to hospital. The key different here is that there may be some LSOAs that have no patients included in the patient dataset and those that do might not be uniformly distributed (some zones may have more).

These two groups have been selected to allow an assessment of whether the results are any different using a patient population, based on the home postcodes of where the patients live (which have been shown to not be uniformly distributed across WY), compared to the WY population that is represented by the LSOA zones (starting points population weighted LSOA centroids). As can be seen when comparing Maps 4 and 5 there are some locations in WY where there are higher concentrations of THR and TKR patients than others. If the results of the comparison are not statistically significantly different (patient data vs population data) then this

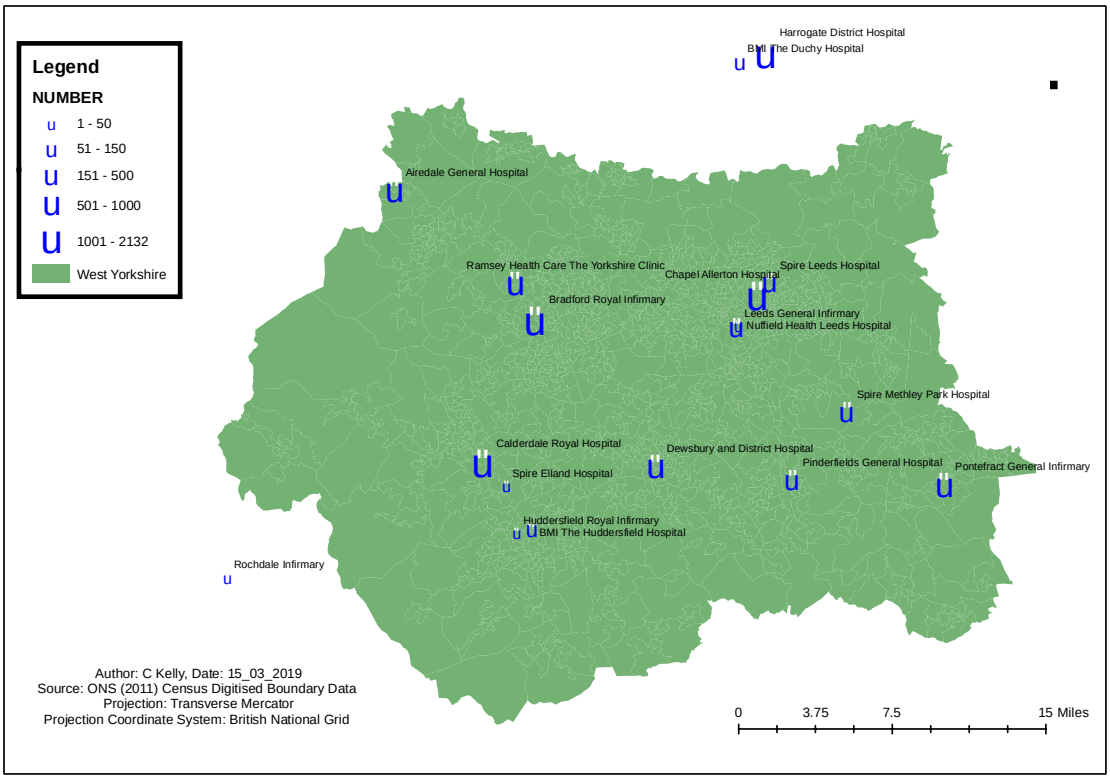
may reduce the need to access the patient data and future analysis could be based on the LSOA zones.



Map 4: Patient data: WY THR and TKR patents (represented on the map as LSOA locations not home postcode to maintain anonymity)



Map 5: Population data: LSOA zones and population weighted centroids in West Yorkshire



Map 6: Hospitals attended by THR and TKR patients

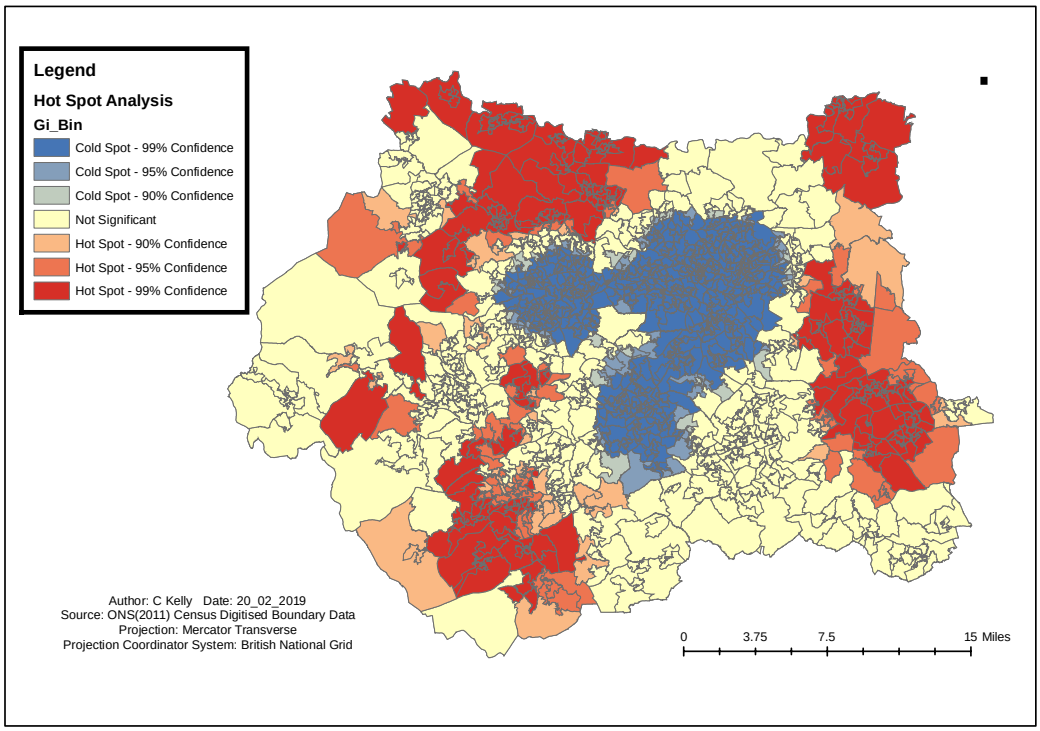
5.2.2 Methodology

The aim was to develop a number of scenarios based on evidence in the literature that could be tested to assess whether they impact negatively or positively on patient travel times and then to assess whether different groups (e.g. across deprivation quintiles) were more or less affected by the changes and in doing so how this might be associated with changes in health outcomes. In doing this it would propose a method that could be applied to assess the impact of policies such as centralisation or reconfigurations of hospital services.

5.2.2.1 Comparing the patient data and West Yorkshire LSOA

The study used two approaches to assess whether there are any differences in using patient's data vs assuming that patients are uniformly distributed across the LSOA zones in the WY region to calculate distances and travel times to a subset of the healthcare facilities. If planning where specific patients attend healthcare facilities is the main aim then using the patient dataset would be the 'correct' approach. As this thesis has shown patients with OA or RA have different characteristics to the general population and are not uniformly distributed across a region, as shown by the arthritis calculator and maps in this chapter.

There were twenty LSOA zones that had no records of a patients having a THR or TKR. The average patients who had undergone a TKR or THR per zone was 7.51 with a range of 0 – 27 patients and standard deviation of 4.26. It can be seen that there are some significant differences with the two datasets when testing for statistically significant hotspots in the West Yorkshire Data using the number of patients per LSOA. Map 7 shows the hot spot analysis results for the patient data by LSOA in WY. The map shows statistically significant spatial clusters of high values (hot spots) and low values (cold spots). As can be seen there are some definite differences across the LSOA in WY. With a number of areas with statistically significant high number of patients (in the red colour) mostly on the boundaries of the WY region and large areas with low numbers of patients in each LSOA (the blue area) in the centre.



Map 7: Hot spot analysis of number of patients having a THR and TKR in West Yorkshire by LSOA

5.2.2.2 Calculating the travel times for the scenarios

The travel times to hospitals were calculated based on the scenarios developed in this chapter and methods described in Chapter 3. The scenarios were operationalized using a combination of software packages. ARCGIS 10.4 was used to implement Location- Allocation models and calculate the changes in travel time by car and Visography Tracc to calculate changes in travel time by bus. Calculating the travel times for the different scenarios used the same methodology as in Chapter 3, road network travel times as a proxy for journey times by car and bus travel times using bus schedules and bus stops.

To be able to optimise the hospitals that the patients or population would attend required a different set of tools. This study used the Location-Allocation models, which are described below in more detail. An extensive body of literature has focused on using Location-Allocation models to identify optimal locations for schools, fire stations and hospitals, with the aim of finding optimal locations that minimises the overall distance travelled by individuals. Rahman and Smith (2000) reviewed the use of Location-Allocation models for healthcare facilities in developing countries and found that the studies had been used to identify optimal locations for new facilities (ex- ante) , evaluate whether previous location decisions had proved to be

effective (ex-post) and to provide alternative options that would potentially have been better. Other literature including Daskin and Dean (2004) and Afshari and Peng (2014) have reviewed the Location- Allocation literature for healthcare facilities.

The Location-Allocation method uses algorithms to optimise the location for a given set of facilities. This works with candidate facilities (e.g. hospitals) and demand points (e.g. patients home locations) and from this chooses a subset of the hospitals (i.e. the user can specify the number of hospitals to be operational) that minimises the distance (using the road network). It is possible to restrict the maximum distances/ travel times that patients can travel (so identifying locations that patients would not be able to get to). There are options to allow one or multiple hospitals to be selected to minimise the distances or travel times. The process works by producing an origin-destination matrix using the shortest distance between each of the hospitals and patient's home locations. This matrix is then adjusted using Hillsman editing (using a p-median structure), (Hillsman, 1984), which enables the solver heuristic (location – allocation solver) to create a number of solutions refined using the Teitz and Bart (1968) vertex substitution heuristic. These solutions are then combined using a meta-analysis to create better solutions and when the program cannot find any improvements it presents the 'best' solution identified. The outputs from this method are the hospitals that have been selected (as the optimal locations), whereby patients have been 'optimally' allocated to each hospital and the travel times using the road network that each individual would have to travel under this scenario. This method can be used to operationalise a number of the potential scenarios, where a restricted set of hospitals is being tested.

5.2.2.3 Assessing how accessibility has changed

Once the optimisation process has been completed a second critical phase is needed to determine whether accessibility for individuals has changed and whether this differs by different groups in society (in order to focus on inequalities). The study has focused on measuring travel time thresholds. The thresholds relate to the models in Chapter 3 and 4 for car of < 10 minutes and > 30 minutes, as they are the two extremes categories for the models applied in Chapter 3 and Chapter 4 (categories of <10 mins, 10 – 20 , 20 -30 and > 30 minutes). The cut offs used for car travel would not have been suitable for the travel times by bus (due to the longer travel times) and so the cuts off for the thresholds used in UK policy for measuring how 'accessible' hospitals are by bus of 60 mins and 120mins have been used. This was previously discussed in Chapter 1.

In addition an assessment for each scenario of how many of the patients (using the data in Chapter 3) would have to travel < 10 minutes and > 30 minutes, as a comparator and more specifically how many under each scenario and patient characteristics (e.g. deprivation quintiles) would have to travel < 10 minutes and > 30 minutes to assess for inequalities.

5.2.2.4 Predicting the health outcomes

The final stage of the methodology is to use the models developed in Chapter 3 to predict the impact on health outcomes from changing where the patients access the healthcare facilities from the differing scenarios. The study is using four of the models described from Chapter 3 to predict what would happen to the health outcomes if the patients in the WY case study (HES-PROMS and OA population) attended a range of different healthcare facilities. These models are:

- LoS for THR (see results Table 42)
- LoS for TKR (see results Table 42)
- OHS (see results Table 40)
- OKS (see results Table 38)

The models with travel times as a categorical variable (0 – 10, 10 – 20, 20 – 30 > 30 mins), were selected as they were found to have a higher R^2 and lower RMSE than the models with travel time as a continuous variable. The prediction model uses the results of the models (LoS and OHS/OKS) and applies them to the new data, which include the following potentially altered explanatory variables: altered travel times (as patients may now be attending a new hospital than previously), altered quality of hospital (as the quality of hospital that the patient is now attending might be different) and finally altered hospital provider (as they may previously have attended a private hospital). The predicted health outcomes were calculated in STATA 15 and involved running the models, dropping the old variables and predicting the expected health outcomes for each of the patients using the new variables determined by the different scenarios (including altered travel times, quality of hospital and hospital provider) using the PREDICT () function. The results are presented by comparing the average health outcomes by scenario, range and 95% CI.

5.2.3 Estimating those with and without a car

The analysis in Chapter 4 identified that there are groups of people that are more likely to find it harder to access a hospital and thus be most affected by changes in where hospitals are

located. This is the group without access to a car and who answered that is was not 'Very Easy' to access the hospital. In England 25.8% of households do not own a car and this rises to 29.4% in WY and ranges from 32% in Leeds to 26% in Kirklees (ONS, 2016a). Finding it harder to access the GP or hospital was uniformly associated with poorer health and well-being outcomes (worse general health category, lower CASP-19 score and a push towards having 'caseworthy' symptoms of depression (see chapter 4). It is therefore critical to try and identify who these individuals are if a targeted approach to restructuring healthcare services is going to minimise inequalities.

Chapter 4 identified that whilst travel distance/ time to healthcare was associated with whether individuals perceived it harder to access the GP and hospital, there were other transport related factors that were key to the rhetoric of understanding what it was that made it harder to access healthcare facilities. One of these has been not having access to a car. For example, the Social Exclusion Unit (2003) estimated that "31% of people without a car have difficulties travelling to their local hospital, compared to 17% of people with a car (p2). Not having data on how patients travelled was one of the main limitations of the HES – PROMS data used in Chapter 3. The results of Chapter 4 showed that individuals without access to a car when needed had lower CASP-19 score, higher odds of being in a worse general health category and higher odds of having 'caseworthy' symptoms of depression. Similarly those who stated that it was harder to access the hospital where more likely to have poorer health outcomes. In order to try and incorporate this critical element into the analysis it is useful to estimate which individuals were more likely to not own a car and therefore be more likely to find it harder to access the healthcare facilities.

In order to estimate which patients are more likely to not have access to a car in the WY patient population the study made use of the predictors of not having access to a car/ van when needed from the ELSA population in Chapter 4 that were also common to the HES-PROMS WY dataset. The variables included gender, age groups (< 60, 60 – 80 and > 80), living alone, residential deprivation quintiles, comorbidities and ethnic group. This estimation was completed using the missing data methodology described in Chapter 3. The subset of ELSA data, with the following variables - gender, age groups, living arrangements, comorbidities, deprivation quintiles, ethnic group and car availability was appended to the HES-PROMS WY dataset. The only variable that wasn't common was car availability that was being estimated and was treated as missing in the HES-PROMS dataset. Essentially not having access to a car when needed is treated as missing in the HES-PROMS dataset and estimated using the variables in the ELSA dataset and STATA code in Box 2. This process was completed using all the ELSA data and then

separately the ELSA data for those individuals that have OA, as Chapter 4 found that groups had slightly different characteristics to the complete ELSA population.

Missing data code for imputing having access to a car

```
mi set mlong

set seed 2018

mi register imputed SPCar

mi register regular sex Agegroups living ethnicity Deprivation_Quintiles Comorbidities

mi impute chained(logit) SPCar = sex i.Agegroups i.Deprivation_Quintiles living_arrangement ethnicity i.comorbities, add (30) dots
```

Box 2: Missing data code to estimate who doesn't have a car

For the patient population 30 iterations were completed each with 10,785 imputations. The percentage of the population that was estimated to not have a car ranged from 15.54% to 18.48% with an average of 17.22 % across the iterations when measured using the complete ELSA data and 15.54% to 20.02% with an average of 17.53% when the sub group of OA ELSA participants was used.

5.2.4 Developing the Scenarios

The scenarios were developed using the literature for reconfiguring where THR and TKR patients could attend hospital. As noted by Barret (2012) there needs to be an increased focus on access to healthcare as one of the drivers of service reconfiguration. These scenarios focus on reconfiguration from this perspective. The scenarios are summarized in Table 71 and described below.

The Current Scenario is based on the results of the case study in Chapter 3. It assumes that there is no change in where patients in WY access their healthcare facilities, across 31 hospitals.

Scenario 1 is focusing on building a new hospital, as has been proposed in a number of case studies around the UK and recently in Leeds in WY. It focuses purely on a location that would minimise travel times, with accessibility as the driver for the reconfiguration. The results from Chapter 3 showed that travelling > 30 minutes to the hospital was associated with poorer health

outcomes, so by limiting the number of hospital to one centralised location it would result in the is one location that would minimise this across the WY region.

Scenario 2 is focusing on reconfiguring all the services to one existing location. Examples of this in the literature include Heart of England Foundation Trust (2014) , where the health authority configured to just one hospital in the region undertaking elective orthopaedic surgery. The difference here is that the accessibility analysis Is one of the driving factors is being undertaken first.

Scenario 3 requires patients to attend their nearest hospital for their THR or TKR. This is removing the choice of hospital. The aim of this scenario is to assess what would happen if travel times were minimised for all patients (as they would all be travelling to their nearest hospital).

Scenario 4(a-g) + Scenario 5 is drawing from the literature that shows that improved health outcomes are associated with the reconfiguration of health services that increase the volume of patients treated at a hospital. This was the justification for the reconfiguration of stroke care at 5 sites in WY. The literature has also shown that increased volume of patients has better health outcomes for patients undergoing a THR or TKR. Each of these scenario test which from a transport accessibility driving force perspective would minimise the travel times for the patient's population if centralisation at one hospital was the focus of the reconfiguration. As in the case of the WY stroke care reconfiguration example, the providers currently undertaking the largest number of THR or TKR have been selected for the scenario. Scenario 5 discusses in more detail which of the 7 hospitals would be the one that minimises travel times.

Scenario 6 Focuses on the impact on travel times from reconfiguring at two of the largest current providers of THR and TKR. This is similar in nature to the Manchester stroke care which changed from providing care at 12 hospitals in the region to 1 24/7 hospital and 2 part time opening hospitals. The focus of the analysis in Morris et al (2014) was the association with health outcomes (mortality and LoS), in this case the aim is to assess whether dropping to two hospitals from 31 affects the travel times that patients would travel for their THR or TKR and be associated with changes in OHS, OKS and LoS in hospital.

Scenario 7 closely resembles the stroke reconfiguration in WY, as the location allocation model is used to select which four hospitals (currently with the largest THR and TKR patients) in the region would minimise travel times, as the driving force between hospital reconfiguration. This is likely to be the most realistic scenario as with a patient load of over 10,000 patients in WY over three years each hospital would need to treat on average 833 patients per year.

The developed scenarios can then be compared with this baseline Scenario. These scenarios were shown to the studies PPI group to get feedback. They were interested in how these different scenarios would affect their access to healthcare facilities. They felt the most realistic was scenario 7 - that reduced the number of hospitals down to four of the main centres that currently provide healthcare and include hospitals that they attended.

For each of the scenarios a comparison is made between the different travel times by car and public transport and using the patient data vs the WY population data. With the patient data an additional assessment is made on the impact on accessibility, the travel times and critically in terms of inequalities, which groups in society (age, gender, ethnicity, living arrangements and residential deprivation levels), would be more or less affected by each of the scenarios. An Assessment is made of the predicted changed in health outcomes from these scenarios and then what would be the impact if the scenarios were based on minimising the travel times for those patients who have been estimated to not have a car.

Table 71: Reconfiguration Scenarios

Scenario	Title	Description
Baseline	Current situation	No changes made to where patients attend healthcare
Scenario 1	A new hospital	If you could start from scratch the one location that would minimise travel times across WY
Scenario 2	One current hospital	This scenario takes the 31 currently attended hospitals and identifies, which one hospital would minimise travel times
Scenario 3	Nearest Hospital	Individuals would be required to attend their nearest hospital
Scenario 4a - g	7 Largest Hospital providers	A comparison between centralising services at each of the 7 largest public providers of hip and knee providers
Scenario 5	One out of 7	Centralising services at one of the 7 largest providers
Scenario 6	2 Hospitals	Centralising services at 2 of the 7 largest providers
Scenario 7	4 hospitals	Centralising services at 4 out of 7 of the largest providers

5.3 Results

5.3.1 Testing the scenarios

For each scenario the travel times by bus and car for each group (WY patient population vs WY population) have been calculated and are summarized in Table 72. This includes the average travel times by car and bus for each scenario by the patient population and WY population LSOA zones. It also summarizes the percentage of patients in the case of the patient population and percentage of zones in the case of the WY population LSOA zones that would not be able to get to a 10 am appointment if leaving by 7 am and travelling by bus.

For the patient population additional analysis focusing on comparisons by the different patient characteristics are summarized in Table 73. In terms of gender, age, deprivation, living alone, being from a non-white British background and what percentage of the population would be travelling < 10 minutes to the hospital and > 30 minutes for each scenario. These results are discussed in more detail in the next sections by scenario.

Table 72: Average travel times by car and bus by scenario and % who could not get there by bus buy 10am if leaving at 7am and walking <800m to the bus stop.

(SD)	Patient population			WY Population (LSOA zones)		
	Car	Bus	% of patients	Car	Bus	% of zones
Current State	14.85 (8.5)	44.12 (23.5)	1.4%	N/A		
Scenario 1	20.62mins (5.91)	81.8 mins (29.07)	1.5%	16.86 mins (5.82)	75.5 mins (30.1)	0.4%
Scenario 2	21.37 (9.46)	73.14 (33.74)	1.38%	19.61 (9.69)	67.41 (33.99)	0.3%
Scenario 3	9.74 (4.45)	26.9 (12.28)	0.8%	7.15 (3.10)	26.5(11.99	0.07%
Scenario 4a	39.72 (13.7)	116.5 (39.6)	27.7%	39.62 (12.58)	119.33 (36.16)	24.8%
Scenario 4b	24.6 (10.7)	85.1 (34.9)	3.2%	23.6 (10.5)	82.3 (34.8)	2.0%
Scenario 4c	24.99 (10.4)	84.26 (37.9)	2%	27.8 (10.99)	79.01 (38.1)	1.1%
Scenario 4d	28.6 (11.8)	98.3 (42.2)	8%	23.34 (10.6)	98.2 (39.9)	5.1%
Scenario 4e	22.6 (8.5)	87.2 (31.3)	1.6%	21.0 (7.9)	82.8 (30.3)	0.2%
Scenario 4f	41.9 (11.1)	113.2 (32.8)	27.6%	41.33 (10.7)	113.1 (31.1)	23.3%
Scenario 4g	33.7 (13.24)	105.4 (44.2)	16.6%	32.7 (11.97)	104.1 (40.8)	12.5%
Scenario 5	22.6 (8.5)	87.2 (31.3)	1.6%	21.0 (7.9)	82.8 (30.3)	0.2%
Scenario 6	18.35 (8.14)	60.1 (27.3)	0.7%	19.01 (7.7)	65.6 (28.9)	0.07%
Scenario 7	13.7 (6.1)	44.95 (21.0)	0.9%	12.9 (5.94)	42.5 (20.4)	0.07%

Table 73: Patient population travelling < 10 mins and >30 mins by car under each the scenario[2]

	mins	Gender		Age (yrs)	Deprivation Quintiles (%)					Living alone	Non White British
		Male	Female	68.3	1	2	3	4	5		
Current status											
All		4,707	6,076	68.3	1,860	1,914	2,169	2,385	2,457	2,917	1,387
Patients	<10	29%	32%	68.6	15.9%	24.1%	29.9%	33.9%	45.1%	33.1%	43.5%
	>30	4.9%	4.8%	66.4	7.0%	7.2%	4.6%	3.2%	3.2%	3.9%	3.39%
Scenario 1 : One new hospital that minimises travel time by car											
	< 10	8.1%	8.0%	67.9	1.3%	5.9%	9.2%	10.0%	12.0%	8.4%	8.1%
	>30	15.6%	14.6%	68.1	25.2%	17.9%	13.0%	11.2%	10.6%	13.4%	13.2%
Scenario 2: One existing hospital that minimises travel times across WY											
Patients	<10	12.8%	14.2%	68.7	5.6%	9.7%	13.9%	13.6%	22.43%	15.8%	16.7%
	>30	20.2%	18.0%	67.8	22.8%	25.7%	20.2%	15.0%	13.6%	17.6%	14.8%
Scenario 3: Attending the nearest hospital											
Patients	<10	57.3%	58.7%	68.3	33.3%	46.7%	59.8%	67.3%	75.3%	66.6%	61.2%
	>30[3]	-	-	-	-	-	-	-	-	-	-
Scenario 4: Centralizing at one of the 7 largest hospitals providing hip and knee replacements											
Airedale	<10	1.3%	1.8%	69.3	2.7%	2.3%	3.1%	0.04%	0.3%	0.02%	0.6%
	>30	76.5%	74.0%	68.34	70.6%	74.7%	74.1%	80.8%	74.2%	74.6%	72.5%
Bradford	<10	8.2%	9.9%	68.1	1%	2.82%	7.8%	11.7%	17.3%	9.5%	17.2%
	>30	31.6%	28.7%	68.0	36.9%	33.0%	27.5%	29.5%	24.9%	26.8%	29.9%
Chapel Allerton	<10	7.7%	10.1%	68.8	5%	21.6%	8.6%	6.0%	16.2%	10.8%	11.6%
	>30	33.7%	31.8%	68.0	36.2%	37.4%	32.4%	32.2%	26.7%	26.5%	27.6%
Calderdale Royal	<10	5.2%	4.9%	68.1	3.5%	5.9%	5.7%	5.6%	4.4%	5.2%	2.2%
	>30	43.4%	44.7%	68.5	58.3%	47.2%	39.2%	35.7%	43.8%	43.0%	43.9%
Dewsbury & District	<10	7.0%	6.6%	67.1	2.4%	7.2%	8.3%	7.6%	7.7%	6.7%	5.6%
	>30	17.2%	18.4%	68.2	31.4%	21.5%	15.9%	12.1%	12.3%	17.3%	13.3%
Harrogate District	<10	--	--	--	--	--	--	--	--	--	--
	>30	87.9%	85.0%	68.1	68.8%	82.4%	88.5%	94.1%	91.2%	85.0%	87.0%
Pontefract	<10	6.3%	5.3%	67.4	2.3%	3.3%	3.3%	9.6%	8.8%	4.6%	6.6%
	>30	62.7%	63.5%	68.7	80.0%	66.7%	63.4%	58.4%	51.7%	64.6%	58.0%
Scenario 6: Centralising at 2 hospitals											
	<10	16%	16.9%	68.7	15.6	15.2	15.4%	18.4%	17.7%	17.9%	19.5
	>30	7.8%	8.3%	68.1	7.5%	9.2%	8.4%	9.3%	6.2%	8.9%	7.6%

[2] Scenario 5 is identical to Scenario 4 Dewsbury and District Hospital.

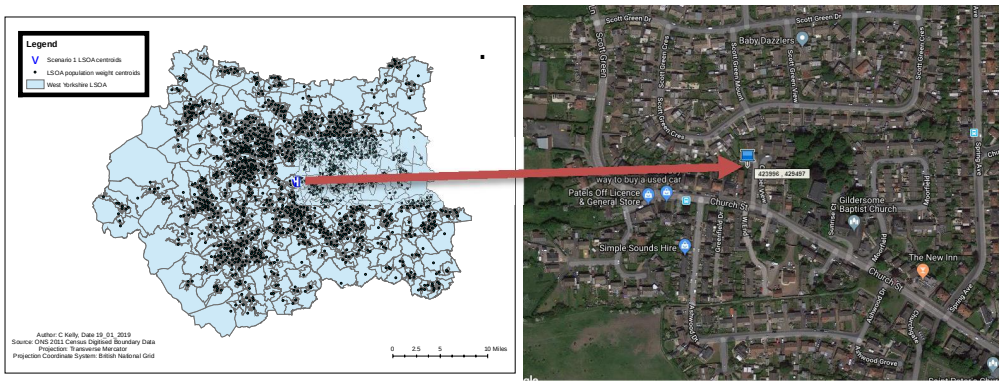
[3] 3 individuals

Scenario 7: Centralising at 4 hospitals											
	<10	32.0%	30.7%	68.1	31.2	32.5	30.2%	32.3%	29.8%	31.2	29.8
	>30	0.02%	0.5%	70.9	0.5%	0.5%	0.4%	0.4	0.3	0.7	0

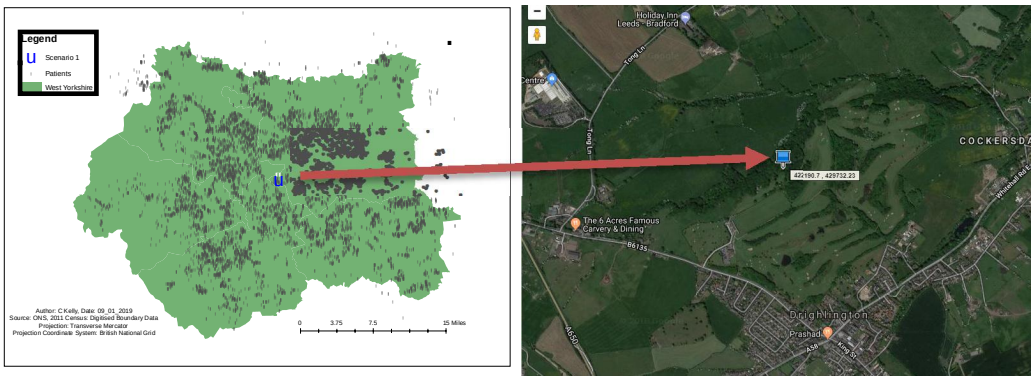
5.3.2 Scenario 1: A new hospital

The first scenario involves finding the optimal location that minimises travel distance to one new hospital across the WY region. Using the WY population (1387 LSOA zones in WY, as the starting location) the optimal hospital location is shown in Map 8. For this location the average travel times by car using the road network are 16.86 mins and range 3.86 – 34.64 mins. If travelling by bus the average bus travel times would be 75.5 mins and range 6.95 – 173.1 mins. Individuals living in 6 out of the 1387 LSOA zones would not be able to access this new hospital for a 10am appointment using the current bus network and schedule, potentially leading to inequalities (there are on average 1614 individuals in each LSOA). As can be seen in Map 9 the optimal location is in the middle of a residential area, so would be less likely to be selected as the location for other practical reasons.

The location identified using the patient population is shown in Map 10 and the aerial photo in Map 11. As can be seen whilst still fairly central it does not give the same location as using the WY population data. Using the patient data the average travel time by car to this location would be 20.62 mins (SD 5.91) and range 6.2 – 40.19 mins. One hundred and fifty six individuals in the patient population could not get to this location by bus (if they left by 7am) for a 10am appointment and the average travel times for those that could would be 81.78 mins (SD 29.07) with a range of 8.73 – 166.41mins (~2.5 hours). Using a comparison between the patient vs population data does give differing results for where the new hospital should be built to minimise travel distances. The average travel time using the WY population data is 16.86 mins compared to 20.62 mins using the patient population, showing a difference for this scenario. This scenario also highlights the differences (or inequalities) between making the journey by car and using public transport. The travel time to make the same journey by bus for the patient population is on average 61.2 mins longer than making the same journey by car. A number of patients would have to leave the house at 7am in the morning to get to the hospital in time for a 10am appointment, with travel times by bus at their highest at 2 hours 46 mins to make the journey using the existing bus schedule and network.



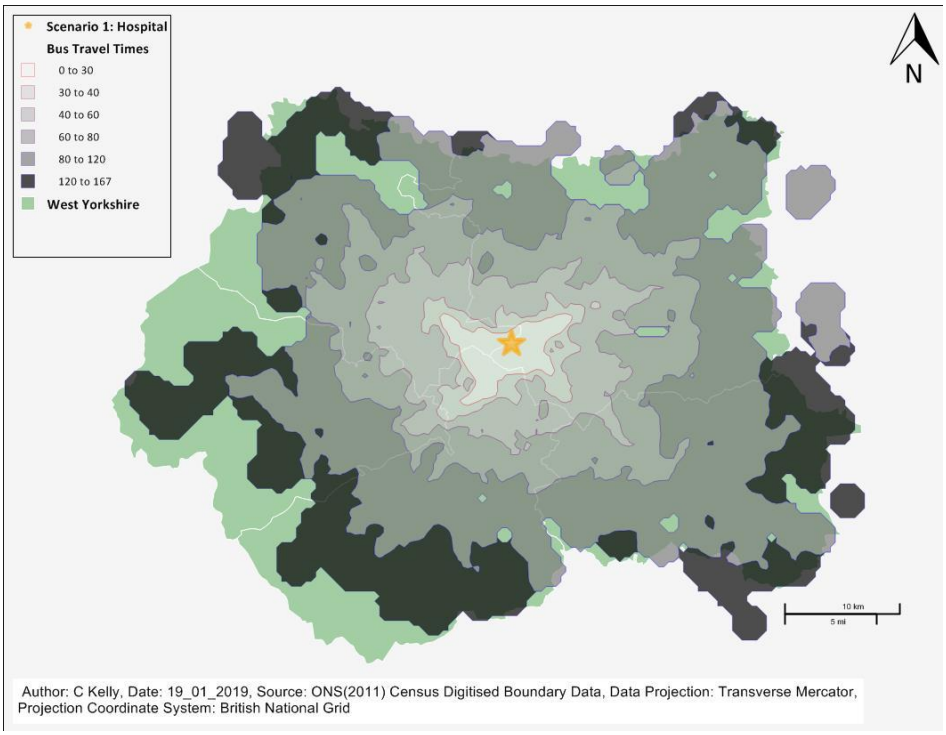
Map 8 & Map 9 : Scenario 1: New hospital location (WY population - LSOA centroids) and Aerial View



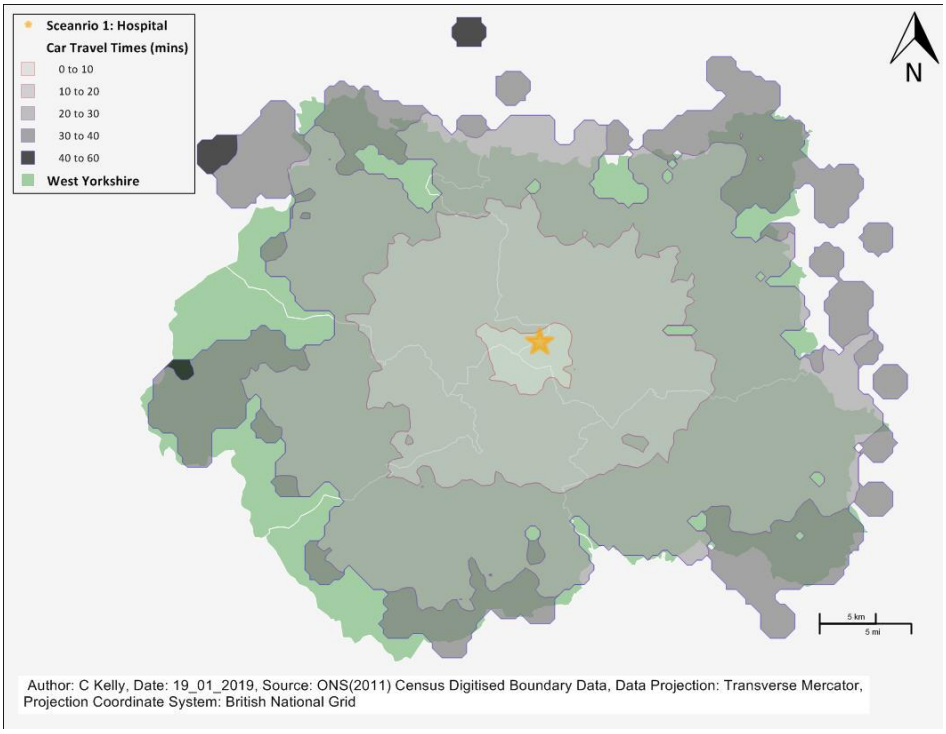
Map 10 & Map 11 : Scenario 1: New hospital location (patient population) and Ariel view

Eighty–five percent of patients could get to the scenario 1 location in 30 minutes or less by car. Following an assessment of the bus travel times only 2.8% of the patients could get to this location by bus/ walk in <30 minutes, 24.9% in <60 minutes and 87.8% in < 2 hours. The travel times by bus to scenario 1 are displayed in Map 12 below. Thus highlighting again the very different accessibility travel times by bus and car. The highest travel time band is 120 – 167 for bus travel times and 40 – 60 minutes for car travel times . When compared against the patient being able to choose where to attend the hospital (current state) Scenario 1 would on average increase travel times by car by an average 5.8 minutes and almost double the travel times by bus to get to the new hospital. Under scenario 1 there would be more patients travelling > 30 mins to the hospital for each of the categories in Table 73. For example, 14.6% of females would be travelling > 30 mins compared to 4.8% in the current state. For those in the most deprived quintile 10.6%, would be travelling > 30 minutes compared to 3.2% under the current status. Thereby highlighting some inequalities due to changing location.

It is unlikely that one new hospital that could cover all the operations needed for THR and TKR in WY, due to the climate of needing to save money, but creating a scenario that is so 'extreme' does show the levels of details that could be employed when thinking about where to locate a facility.



Map 12: Scenario 1: Travel times by bus (mins) (Patient population)

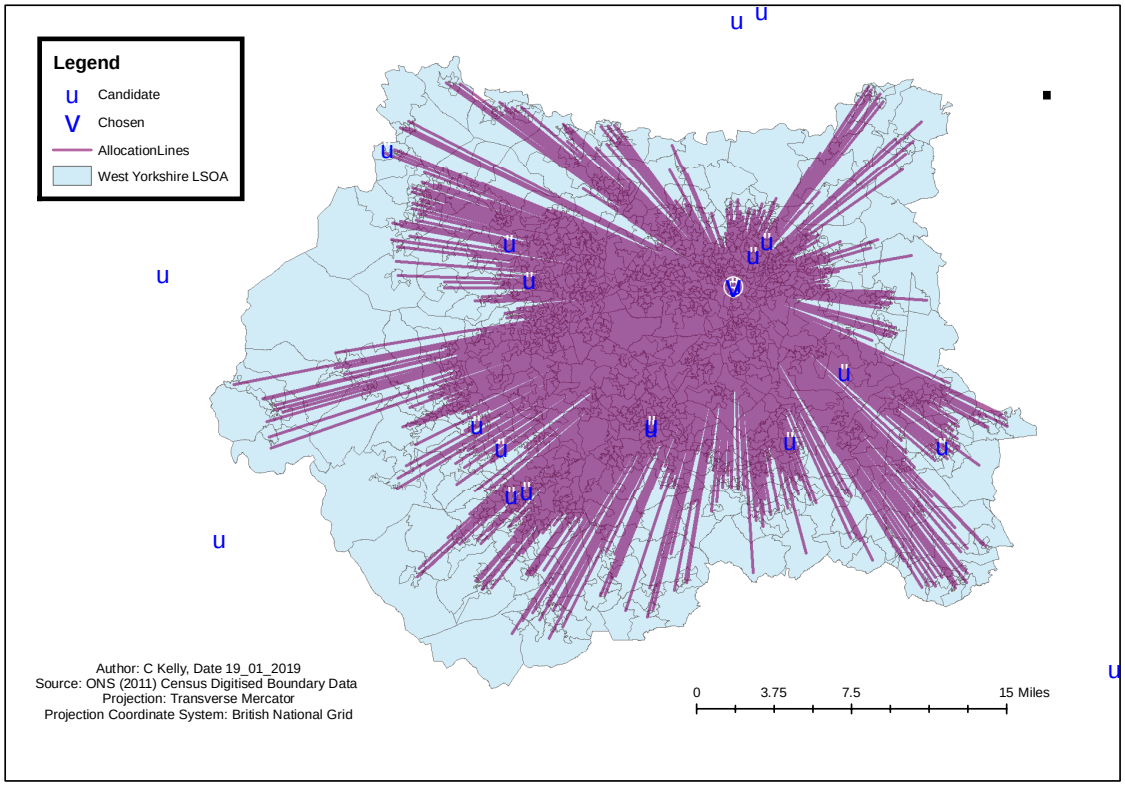


Map 13: Scenario 1: Travel times by car (mins) (Patient Population)

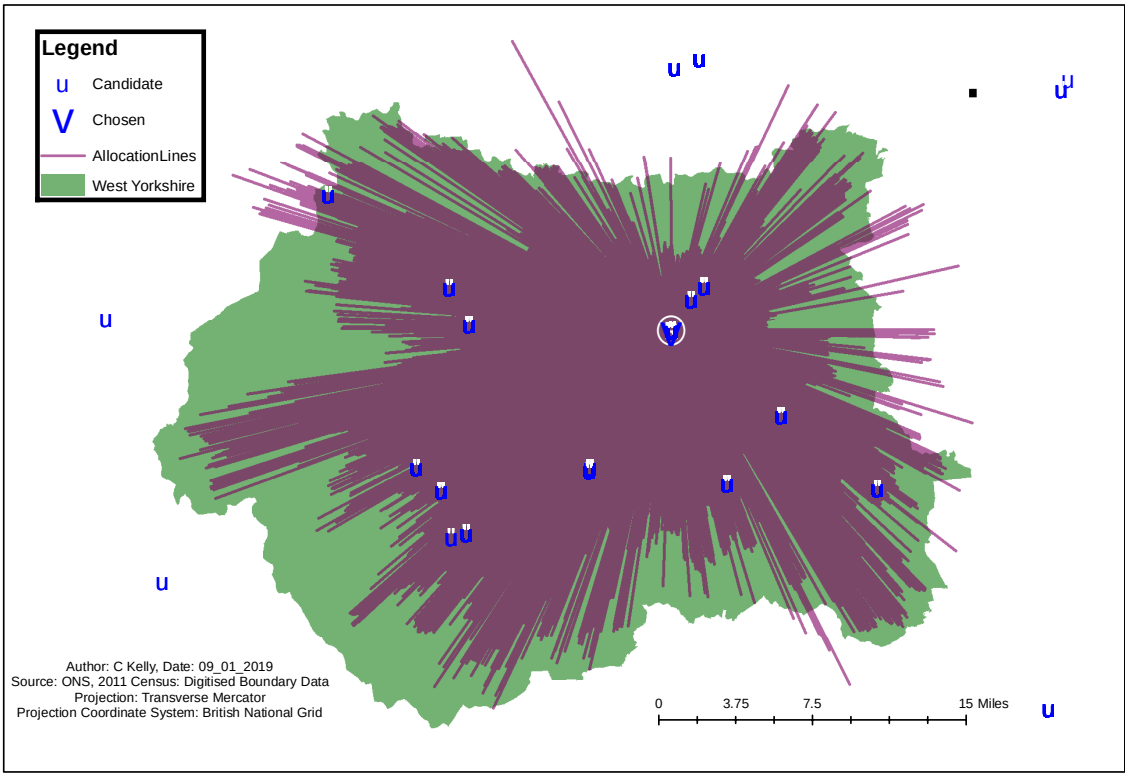
5.3.3 Scenario 2: The one hospital that minimises travel times (out of all 31 hospitals)

Scenario 2 focuses on which one hospital out of the 31 hospitals that were attended by patients in the WY case study in Chapter 3 would minimise travel times for the patient and WY population. Testing Scenario 2 using the WY population data results in the Nuffield Health Leeds Hospital (one of the private hospitals in WY), shown in Map 6 (p 262) as the optimal location. The average travel time to this hospital would be 19.61 mins (SD 9.69) and range 1.6 – 49.8 mins.

The same hospital is selected for scenario 2 when using the patient data, as shown by Map 15. Average travel times to the hospital for the patients would be 21.37 mins, range 0.9 – 56.8. The results show that the same hospital would have been selected using either the WY population and patient data, but that using the WY population data underestimated the travel times for the patient population.

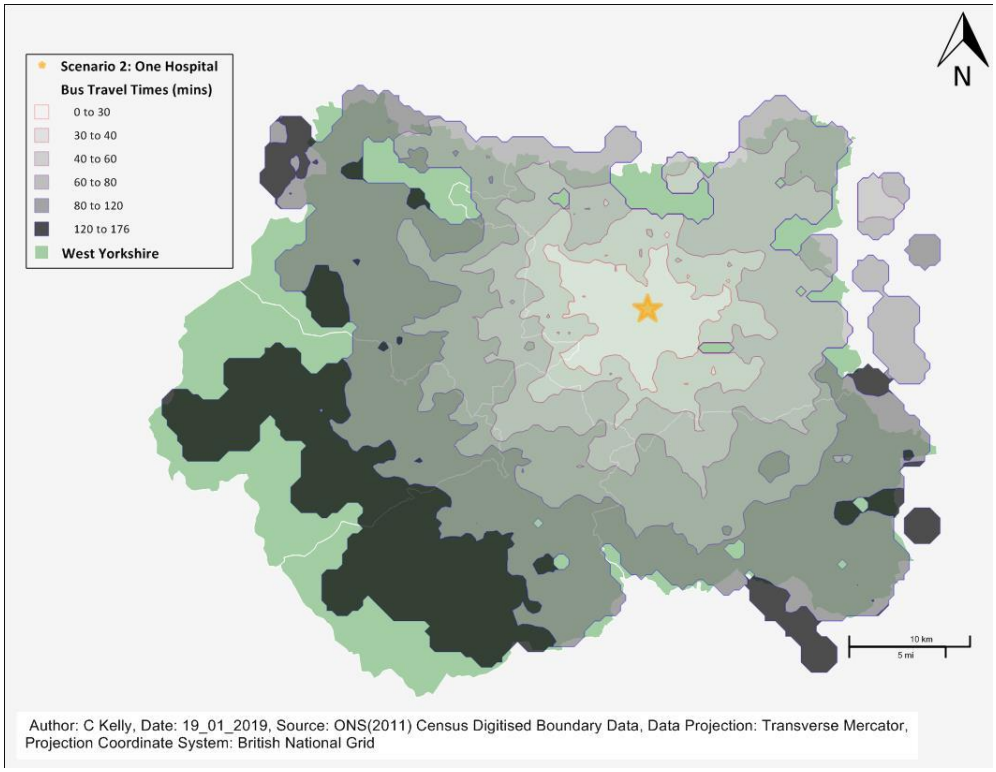


Map 14: Scenario 2: Centralising to one hospital (WY population)



Map 15: Scenario 2: Centralising to one hospital (patient population)

Using the WY population data the average travel time by bus to reach this hospital in Scenario 2 would be 67.41 mins (SD 33.99) range 6.13 – 165.5 mins with individuals in five zones not be able to access the hospital in time for a 10 am appointment. Using the patient data the average travel times by bus would be 73.14mins (SD 33.74) range 6.13 – 165.3mins and 138 patients could not make a 10am appointment across 47 zones. Compared to Scenario 1 the travel times by car are longer, but the travel times by bus have shortened by 10 minutes, indicating that changing where patients access healthcare and improving bus travel times, does not necessarily mean that car travel times will also reduce or vice versa.



Map 16: Scenario 2 - Bus travel times (using the patient population)

In total 81.6% of the patients could access the Nuffield Health Leeds Hospital in <30 minutes. In terms of accessibility 9.3% of individuals could get to the Scenario 2 hospital by bus in under 30 minutes, 53.9% within 60 mins and 89.0% in 120 minutes.

Scenario 2 as shown in Table 73 increases the percentage of patients travelling >30 mins in all groups compared to Scenario 1 with the exception of those in least deprived quintile who have a 3.6% reduction in patients travelling >30 mins. There is also an increase in the percentage of patients in the most deprived quintile travelling <10 minutes to the hospital (so less) compared to the current scenario. On average patients in Scenario 2 would be travelling 6 mins further by car and 29 mins further by bus compared to the current state.

When looking to centralise it is unlikely that a private hospital would be chosen as the candidate hospital. In particular it is likely to not have the equipment, facilities and expertise for operations that are straightforward. This hospital treated 330 patients over the 2009/10 and 2011/12 timeframe (as shown in Table 74) and replaced 260 hips and 477 knees in 2017 (737 in total) ((National Joint Registry, 2017). This makes it less likely that on its own would be able to meet current and future demand alone and an alternative scenario would be preferred. This is a hypothetical scenario, however, given the current hospitals attended by THR and TKR patients in WY it would be the optimal location to minimise travel times if treatment were to be centralised at one current hospital.

5.3.4 Scenario 3: Attending the nearest hospital

The analysis in Chapter 3 indicated that 36% of patients attended their nearest hospital. Scenario 3 minimises travel times by requiring patients to attend their nearest hospital out of the 31 possibilities. It is the one scenario that guarantees that no patients will travel any further than they used to by car (not necessarily by bus). Using the WY population and restricting attendance to travelling to the nearest hospital would reduce the number of hospitals attended down from 31 to 21. A significant drop of over 10 hospitals (approaching 1/3). Applying this Scenario to the patient data results in the same 21 hospitals being selected, as shown in Table 74. Interestingly one of the main hospitals that is selected both from access by car and by bus as the nearest is the Leeds General Infirmary. This hospital only treated 10 of the WY patients in the case study, this is in part due to Chapel Allerton being the main provider for RA and OA patients in Leeds. This scenario may mean that some hospitals that weren't previously THR or TKR specialists, might provide a more optimal location (reduce travel times) for patients to access. Hospitals such as Airedale General Hospital would under this scenario only treat 60% of the WY THR and TKR patients that they actually did treat and others such as Huddersfield who only had one operation in the WY case study would now be allocated 363 patients.

One of the results is that the optimal hospital in Scenario 2 (Nuffield health Leeds Hospital) would not have been selected as the nearest hospital by car using either the patient or WY population data (see table 74), but was identified for some WY zones and patients, as being the nearest in terms of bus travel times.

In Scenario 3 the average travel time by car for the WY population would be 7.15 mins and range 0.94 – 19.88 and average travel time by bus would be 26.5 mins, range 2.67 – 87.61 mins. Only one LSOA zone (coordinates 410480 eastings and 436381 northings) would not able to reach the nearest hospital by bus for a 10 am appointment.

Using the patient data for Scenario 3 would reduce the average travel time by car to 9.74 mins (SD 4.45) and range 0 – 34 mins. It would maximise the ability of patients to attend the hospital by bus. Under this scenario only 0.8% would not be able to access the hospital by bus or walking for a 10 am appointment (if they left their house by 7am). The average travel time for those who could make the journey by bus would be 26.9 mins (SD 12.28) range 0 – 102 mins.

Table 74: Comparison of which hospitals patients attended in the WY case study vs nearest

Hospital	Patients: Current status		Patients nearest hospital by car		WY population nearest by car (zones)	
	No.	%	No.	%	No.	%
Airedale General Hospital	942	8.10	573	5.70	54	3.89
BMI The Duchy Hospital	76	0.65	34	0.34	1	0.07
BMI The Huddersfield	135	1.16	923	9.18	105	7.57
Bradford Royal Infirmary	1179	10.14	1139	11.33	190	13.70
Burnley General Hospital	11	0.09	17	0.17	3	0.22
Calderdale Royal Hospital	2132	18.34	724	7.20	88	6.34
Chapel Allerton Hospital	1486	12.78	499	4.97	88	6.34
City Hospital Campus	2	0.02	0	0.00	0	0.00
Claremont Hospital	1	0.01	0	0.00	0	0.00
Dewsbury and District Hospital	583	5.01	16	0.16	2	0.14
Doncaster Royal Infirmary	19	0.16	0	0.00	0	0.00
Freeman Hospital	1	0.01	0	0.00	0	0.00
Harrogate District Hospital	1908	16.41	169	1.68	14	1.01
Huddersfield Royal Infirmary	1	0.01	363	3.61	39	2.81
James Cook University Hospital	1	0.01	0	0.00	0	0.00
Leeds General Infirmary	10	0.09	1357	13.50	247	17.81
Northern General Hospital	21	0.18	0	0.00	0	0.00
Nuffield Health Leeds Hospital	331	2.85	0	0.00	0	0.00
Nuffield Health York Hospital	3	0.03	0	0.00	0	0.00
Pinderfields General Hospital	412	3.54	591	5.88	88	6.34
Pontefract General Infirmary	929	7.99	786	7.82	93	6.71
The Yorkshire Clinic	888	7.64	1013	10.08	95	6.85
Rochdale Infirmary	2	0.02	48	0.48	8	0.58
Royal Hallamshire Hospital	2	0.02	0	0.00	0	0.00
Royal Orthopaedic Hospital	3	0.03	0	0.00	0	0.00
Spire Leeds	152	1.31	107	1.06	19	1.37
Spire Longlands	58	0.50	907	9.02	157	11.32
Spire Methley Park Hospital	289	2.49	536	5.33	65	4.69
Spire Elland Hospital	37	0.32	248	2.47	31	2.24
Wrightington Hospital	5	0.04	0	0.00	0	0.00
York Hospital	9	0.08	0	0.00	0	0.00

A number of the patients living at the extreme edges of WY would still find that travelling just outside of the region would get them to their nearest hospital. For example, Harrogate hospital is still the fastest hospital to get to for 169 of the patients and Burnley for 17 of the patients by

car. This goes down to 14 patients to Harrogate hospital and 3 to Burnley when looking at which is the nearest by bus travel time.

If individuals attended their nearest hospital 99.9% would get there < 30 minutes by car and 100 % < 40 minutes by car. For the bus journeys if individuals attended their nearest hospital 60.1% of then would be able to get there < 30 minutes bus/ walk journey, 98.0% <60 minutes and 99% <120 minutes. As shown in Table 72 this scenario would reduce average travel times by car to 9.74mins and bus to 26.9mins. Table 73 shows that this scenario maximises the percentage of patients living in the most deprived quintile travelling < 10 minutes (compared to all other scenarios). For those living alone 66.6% would be able to access the nearest hospital in less than 10 minutes.

In terms of centralising care and treatment this scenario does reduce the number of hospitals that patients would be attending (particularly in the WY region) and might be a more realistic option than Scenarios 1 and 2 (focusing on 31 down to 21). The key policy issue will be that currently as discussed in Chapter 1, patients do currently have some choice over where they attend and this scenario would remove this. If looking to cut further the number of locations that patients attend within WY a better scenario might be to focus on centralising at one of the existing largest providers in WY.

5.3.5 Scenario 4: Selecting one of the 7 largest hip and knee replacement providers as a centralised facility

Scenario 4 focuses on the travel times if just one of the existing larger hospitals that provides THR and TKR was selected. This being a more likely scenario than Scenario 1, which would require a new hospital to be built. Or Scenario 2 which identified a private hospital as the optimal location. It is more likely that one of the existing hospitals that currently undertakes a larger number of THR or TKR would become the centralised hospital. In total there are 7 NHS hospitals within WY and Harrogate that over the period 2009/10 – 2011/12 completed over 500 THR and TKR operations, as shown in Table 74. These are: Airedale General Infirmary, Bradford Royal Infirmary, Chapel Allerton Hospital, Calderdale Royal Infirmary, Dewsbury and District Hospital, Harrogate District Hospital and Pontefract General Hospital. Table 75 reports the travel times and distances if all of the patient population attended one of these 7 hospitals. Table 76 shows the same for the WY population data. The hospitals that are least accessible for the patient population and WY population are Harrogate General Hospital followed by Airedale General Hospital. As can be seen in Map 6 (page 262) Harrogate General Hospital is north of the WY boundary and Airedale General Hospital is in the top left of WY. The average travel time to

get to Harrogate hospital is 42 mins and Airedale 40 mins using the patient data. Using the population data (zones) results in lower travel times and distances compared to using the patient data.

The hospital that would minimise average travel time by car for the patients would be Dewsbury District Hospital followed by Chapel Allerton Hospital and Bradford Royal Infirmary. As shown in Table 76 average travel times by car to Dewsbury and District Hospital, would be 23 mins if measured using the patient data and 21 mins if measured using the WY population data. This in on average 10 minutes more than the current state. This would still results in some people travelling > 30 minutes by car. Using the public transport travel times as an indicator of accessibility if you didn't have a car, on average it is quicker to get to Chapel Allerton and Bradford Royal infirmary than Dewsbury District Hospital, but all three were shown to be the most accessible. Airedale and Harrogate had the longest travel times, but also both had over 25% of patients who couldn't get to the hospital by 10am. Critically using the WY population data (zone centroids) as the starting locations did not identify such large numbers of patients who would find it difficult getting to the hospital on time if they didn't have a car.

The hospital to patient ratios (what proportion of individuals can get to that hospital in 30 mins by car and 30 and 60 minutes by bus) for scenario 4 and 5, are provided in

Table 77. The results in Table 73 show that when comparing patient travel times that centralising the hospital treatment at Dewsbury and District hospital would lead to the lowest percentage of patients living in the most deprived quintile travelling over 30 minutes by car at 12.3%. Centralising at Harrogate District Hospital would lead to 91.2% of patients in the most deprived quintile travelling over 30mins, but less (68.8%) of those in the least deprived quintile travelling over 30 mins. Centralising at Chapel Allerton hospital would lead to the highest percentage of women travelling less than 10 mins to the hospital. Centralising at Bradford Royal Infirmary would lead to the highest percentage of men travelling less than 10mins to the hospital. There are definitely differences across the 7 hospitals by the different groups and inequalities in the times that patients would need to travel.

Table 75: Travel times and distances to the 7 largest hip and knee replacement hospitals using patient data.

		Road Distance (Miles)	Road Travel time (mins)	Bus & walk Travel Time (mins)	Number who couldn't get there by 10am
Current State	Average	7.23	14.85 (8.5)	44.12 (23.5)	150 (1.4%)
	Range	0.01 -115.50	0.10 – 175.99	0.24 – 170.81	
Airedale General Hospital	Average	21.08 (8.21)	39.72 (13.65)	116.51 (39.6)	2,784 (27.7%)
	Range	0.29 – 42.21	2.54 – 77.24	4.2 – 171.8	
Bradford Royal Infirmary	Average	12.90 (6.47)	24.63 (10.70)	85.06 (34.9)	323 (3.2%)
	Range	0 – 31.36	0 – 57.72	0.24 – 175.83	
Chapel Allerton Hospital	Average	13.81 (6.39)	24.99 (10.37)	84.26 (37.87)	247 (2%)
	Range	0.36 – 33.69	1.33 – 62.27	4.72 – 180	
Calderdale Royal Infirmary	Average	15.62 (7.37)	28.56 (11.78)	98.32 (42.16)	810 (8%)
	Range	0.18 – 35.59	1.34 – 62.83	2.87 – 176.05	
Dewsbury and District Hospital	Average	12.34 (5.04)	22.62 (8.49)	87.22 (31.26)	163 (1.6%)
	Range	0.15 – 28.80	0.77 – 57.74	1.68 – 179.26	
Harrogate District Hospital	Average	23.75 (6.68)	41.89 (11.14)	113.19 (32.8)	2,775 (27.6%)
	Range	6.34 – 42.53	12.82 – 79.56	18.13 – 176.0	
Pontefract General Hospital	Average	19.91 (8.45)	33.68 (13.24)	105.38 (44.2)	1,665 (16.6%)
	Range	0.19 – 41.14	0.96 – 77.62	4.25 – 180	

Table 76: Travel times and distances to the 7 largest hip and knee replacement hospitals using WY population data

		Road Distance (Miles)	Road Travel time (mins)	Bus Travel Time (mins)	Number of zones who couldn't get there by 10am
Airedale General Hospital	Average	21.04 (7.54)	39.62 (12.58)	119.33 (36.16)	344
	Range	0.48 – 41.16	2.63 – 76.77	4.12 – 170.1	
Bradford Royal Infirmary	Average	12.33 (6.30)	23.62 (10.50)	82.26 (34.78)	28
	Range	0.27 30.31	1.45 – 54.25	2.92 – 175.77	
Chapel Allerton Hospital	Average	15.20 (6.87)	27.78 (10.99)	79.01 (38.07)	16
	Range	0.30 – 32.36	1.86 – 57.00	3.17 – 174.58	
Calderdale Royal Infirmary	Average	12.89 (6.56)	23.34 (10.61)	98.17 (39.86)	71
	Range	0.40 – 33.59	1.40 – 55.29	4.04 – 170.45	
Dewsbury and District Hospital	Average	11.45 (4.71)	21.03 (7.92)	82.75 (30.26)	3
	Range	0.32 – 25.74	1.28 – 44.43	3.58 – 162.85	
Harrogate District Hospital	Average	23.45 (6.45)	41.33 (10.72)	113.09 (31.07)	324
	Range	7.41 – 42.42	14.06 – 72.59	18.07 – 170.46	
Pontefract General Hospital	Average	19.41 (7.72)	32.70 (11.97)	104.13 (40.77)	173
	Range	0.45 – 40.78	1.72 – 65.39	4.16 – 179.84	

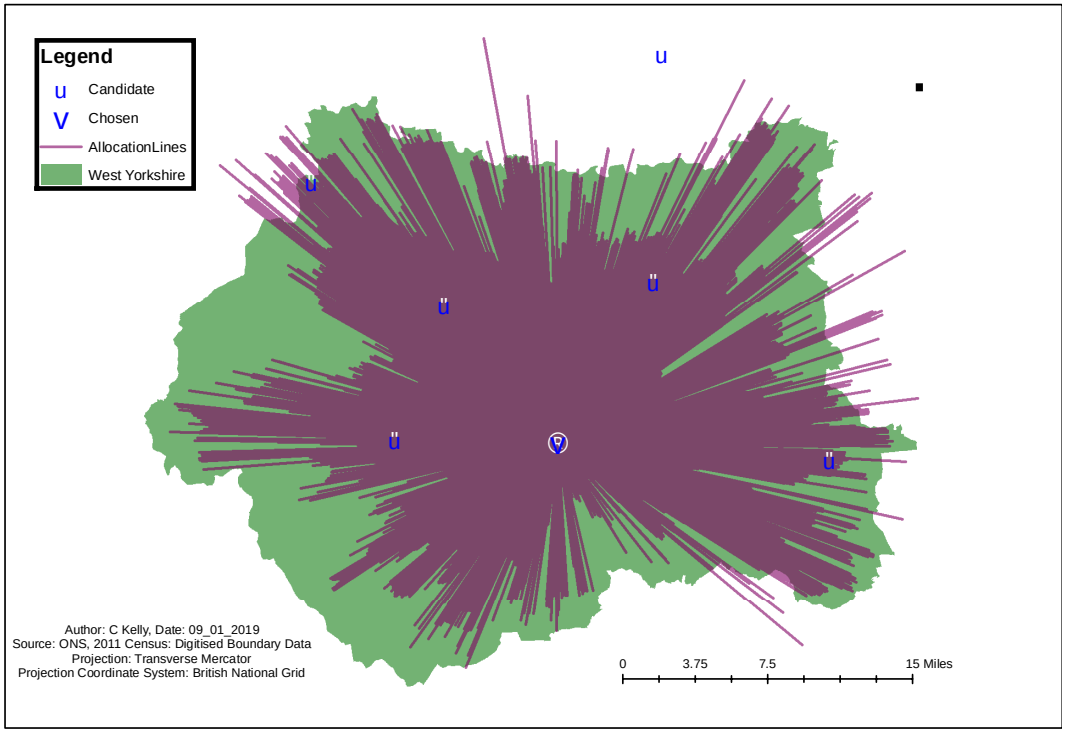
Table 77: Accessibility index ratios.

	Patients in time catchment < 30 mins By Car	Patients in catchment < 30 mins bus	Patients in catchment < 60 mins bus
1 Harrogate	1,524	95	548
2 Chapel Allerton	7,266	700	3,142
3 Bradford Royal Infirmary	7,555	683	2,756
4 Calderdale Royal Infirmary	6,019	702	2,118
5 Dewsbury and District	8,856	423	1988
6 Airedale	2,685	309	884
7 Pontefract Royal Infirmary	3,975	643	1628

5.3.6 Scenario 5: The one hospital (out of the largest 7 providers that minimises travel times)

Scenario 4 focused on access to each of the 7 hospitals, whereas scenario 5 uses the Location - allocation model to determine which one hospital would be selected if the aim was to minimise travel times to one of the seven hospitals. The Location-Allocation model selected Dewsbury and District Hospital (as expected as the optimal location under Scenario 4 by travel time) to send all the patients to as shown in Map 17 if only one hospital out of the seven was to be selected. The same was selected for the WY population data. For average travel times see Table 75 and 76 for this scenario.

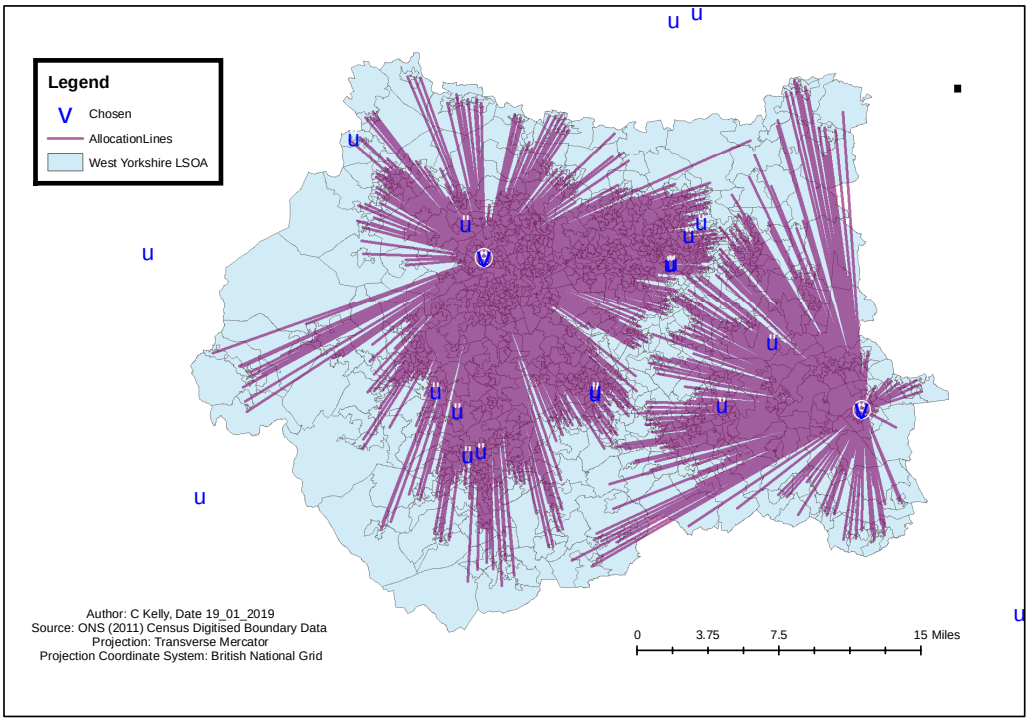
Given the larger numbers of patients expected to require THR and TKR in the future due to an ageing population it is more likely that multiple hospital sites would be needed to cover the demand for THR and TKR and Location- Allocation models can help with this process.



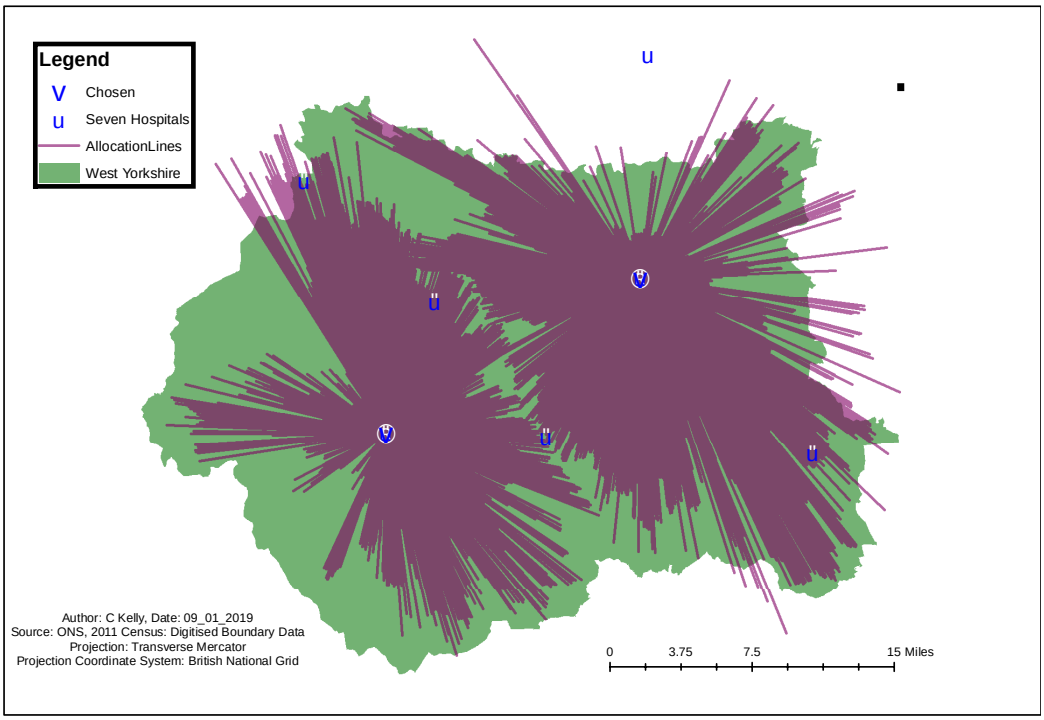
Map 17: Centralising to one of the 7 largest hospitals (WY patient data)

5.3.7 Scenario 6: Optimising across two hospitals

As one of the key issues identified in Chapter 1 is that the demand for THR and TKR are expected to increase with the increasing population over the age of 50. It is more likely that one hospital will not be able to meet this future demand alone. The next scenario is to optimise the travel times to more than one hospital. The Location-Allocation function in ARCGIS 10.4 was programmed to minimise the travel times (using the road network) to two locations for scenario 6 out of the 7 possible larger NHS hospital. Using the WY population data the Location-Allocation method identified that the two hospitals that minimised travel times by car were Bradford Royal Infirmary and Pontefract Hospital (see Map 18 and hospitals listed as chosen).



Map 18: Minimising travel time to 2 hospitals (using WY population data)



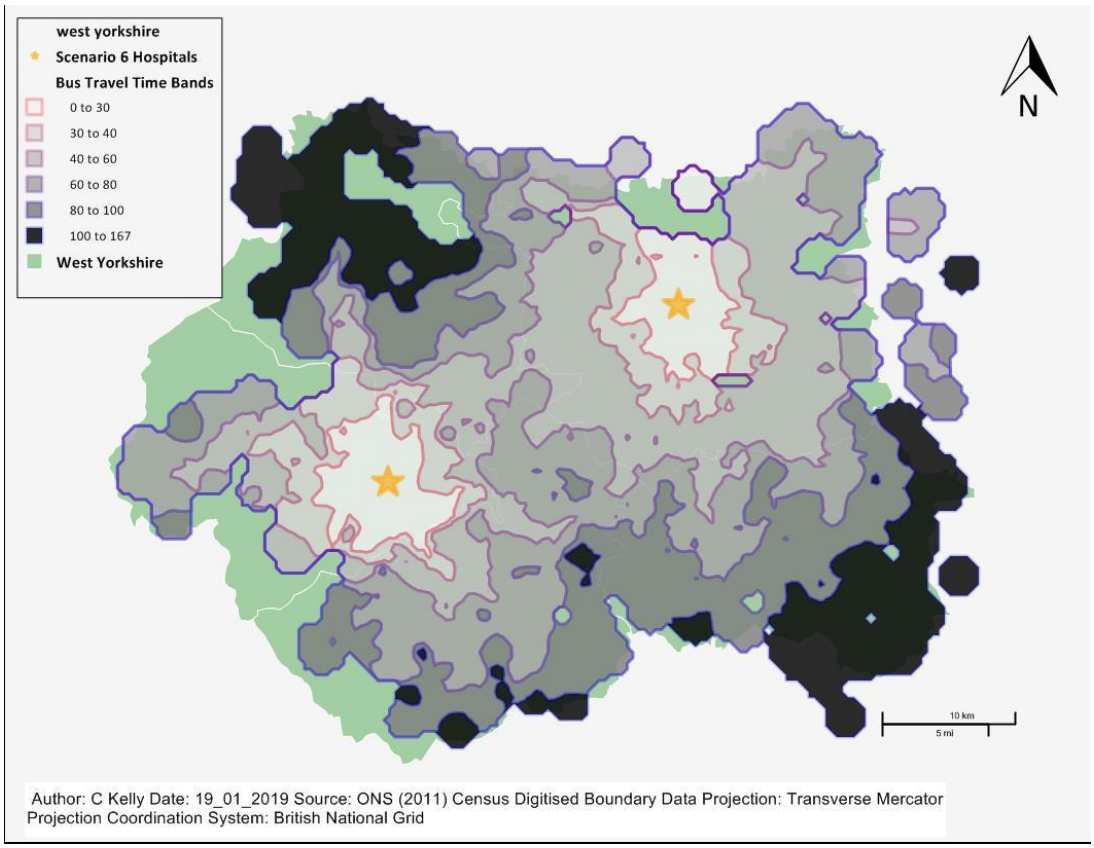
Map 19: Centralising services over 2 Hospitals (patient data)

Using the patient data the model selected Chapel Allerton Hospital (Location3) and Calderdale Royal Hospital as the two hospitals that would minimise road network travel time (Map 19). The

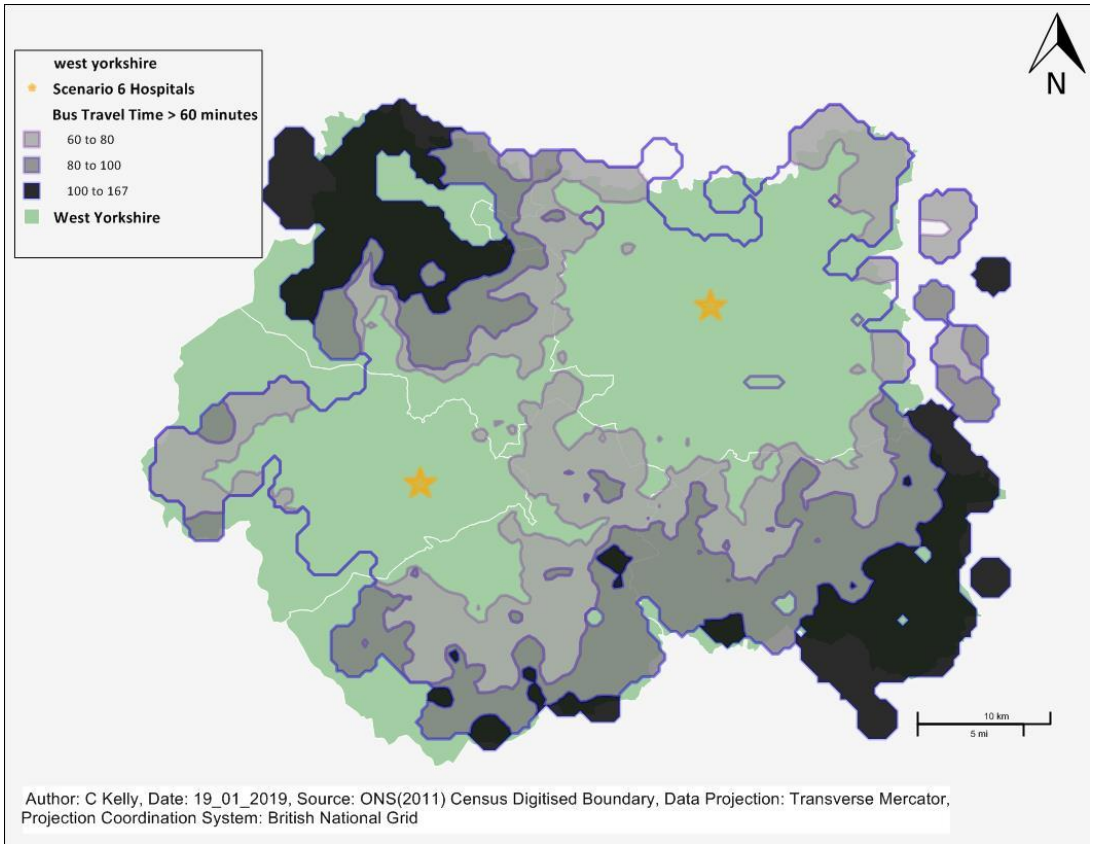
average travel time using this option is 18.35 mins by car and distance 9.67miles. With the average travel time to Chapel Allerton Hospital at 19.09 mins and Calderdale Royal Hospital 17.43 mins by car. The results of this model are shown in Map 19.

Under the scenario of centralising services across two hospitals different hospitals are selected as the optimal hospitals for the patient vs WY population. This is partly reflective of patients not being uniformly located across the LSOA zones. This should be expected given the age and gender profile of patients who undergo THR and TKR, as described in Chapter 3 differs from the general population in age, gender etc… Given the very specific characteristics of this type of treatment it may increase the argument for using patient data in these type of analysis and decision making processes.

When calculating the travel times by bus for the patients to these 2 locations (assuming that individuals attended the nearest out of the two hospitals) 72 patients could not get to either of the 2 hospitals for a 10am appointment. Using the patient data the average travel time by bus for those who could attended was 60.1 mins. Using the WY population LSOA zones the average travel times by bus would be 65.6mins. The distributions of travel times by bus are presented in Map 20 for the 2 hospitals for the patient data. Map 21 shows those locations that could not get to the hospitals < 60 minutes of bus travel, so identifying potential pockets of inaccessibility. It is not just those on the periphery of the region that have longer travel times by buses. A number of pockets where accessibility is limited can be identified from the maps closer to the centre.



Map 20: Scenario 6: Travel times by bus to the 2 hospitals (patient data))

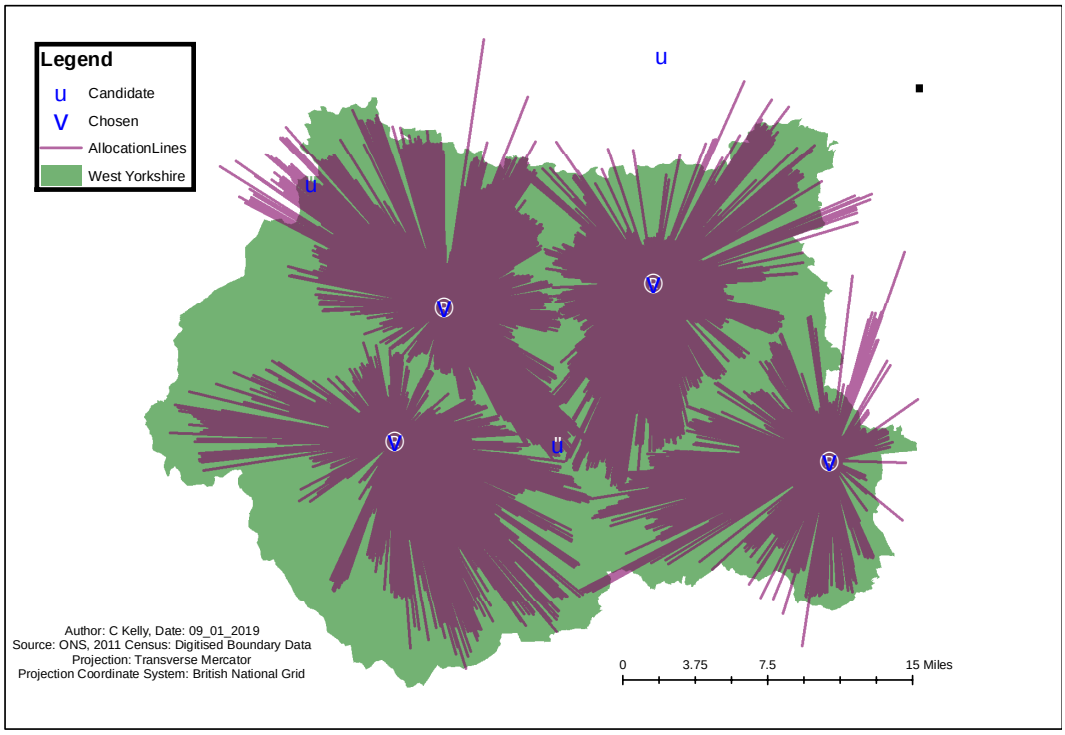


Map 21: Scenario 6: Locations in WY that could not get to either of the 2 hospitals within 60 mins by bus (patient data

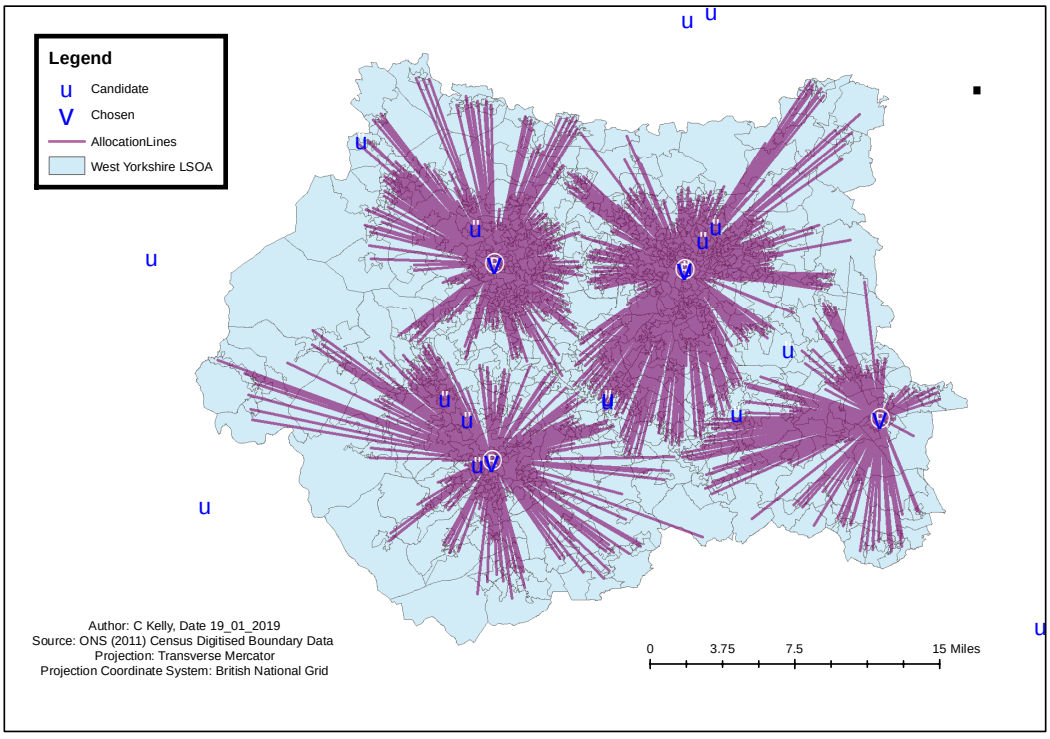
5.3.8 Scenario 7: Centralising over 4 hospitals

To meet a growing demand it may be necessary and more realistic to select more than 2 hospitals for the WY region and Scenario 7 tests this by selecting four hospitals out of the largest 7. The Location- Allocation model selected Bradford Royal Infirmary (location2), Chapel Allerton Hospital (location 3) and Calderdale Royal Hospital (location4) and Pontefract Hospital (location 7) to minimise the overall travel times. Both the WY population and patient data optimisation selected the same 4 hospitals out of 7, as shown in Map 23 and Map 22. Under Scenario 7 the average travel time would be 13.67 mins and average total distance 6.71 miles) using the patient data. Compared to the current state this reduces the average travel times by car. Using the WY population data the average travel time across the 4 hospitals would be 12.90 mins and range 1.2 – 31.92 mins.

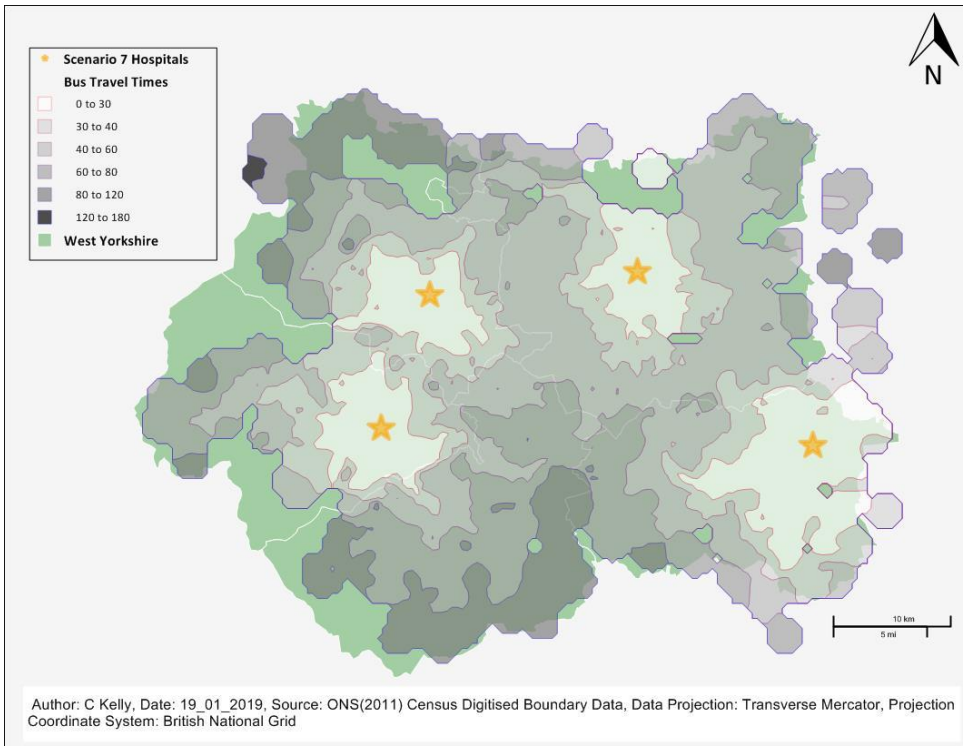
Calculating the travel times by bus for the patient population for Scenario 7, average bus journeys of 44.95 mins (SD 21.02) and range 1.25 – 128.34. Ninety-Four patients could not reach and of the 4 hospitals in the timeframe. For the calculations using the WY population only 1 LSOA zone could not reach at least one of these 4 hospitals within the given timeframe of an appointment at 10 am in the morning. The average travel times would be 42.49 mins and range 2.86 – 114.7 mins. The distributions shows how long it would take to get to the nearest of the 4 hospitals by bus using the patient data are provided in Map 24. Map 24 shows those patients that would have travel times > 60 minutes by bus. Therefore identify potential geographical regions where more support to access healthcare would be needed.



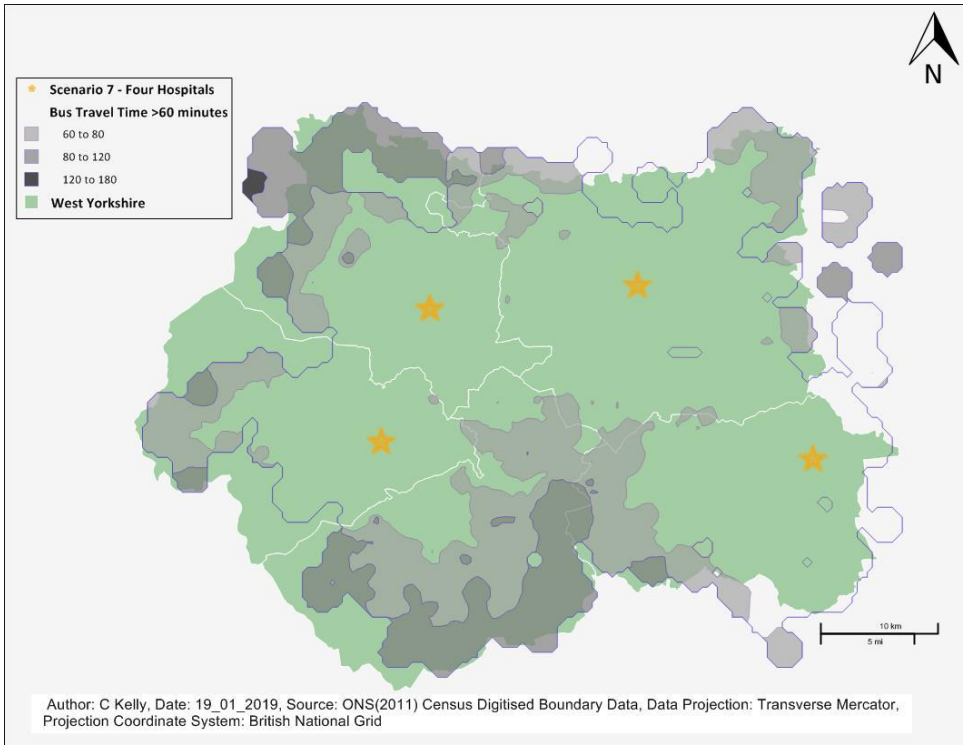
Map 22: Scenario 7: Centralising services over 4 hospitals (Patient Population)



Map 23: Scenario 7: Centralising services over 4 hospitals (WY population)



Map 24: Scenario 7: Travel times by bus to the 4 hospitals



Map 25: Scenario 7: Areas that could not get to any of the hospitals by bus within 60 minutes

As summarized in Table 72 this scenario reduces the average travel times by car compared to all other scenarios (with the exception of scenario 3 - nearest hospital) including the current state. It does the same for bus travel times and has only marginally longer average bus travel times

than the nearest hospital. The results show that only 0.3% of patients would have to travel by car for over 30 minutes to get to one of these hospitals. A large reduction compared to some of the alternative scenarios.

5.3.9 Summary of the scenarios

A number of scenarios have been tested to see whether this type of data could be usefully used as a mechanism for prioritising future resources. One of the key findings from Chapter 3 was that it was actually the individuals living closest and furthest away from the hospital that had the worst health outcomes. Using these scenarios we can have a look to assess whether the characteristics of the individuals fitting into the > 30 mins and < 10 mins brackets change dependent on the model used, as shown in Table 73.

Focusing on the scenarios by group. Chapter 3 of this thesis identified that women were more likely than men to find accessing the hospital more difficult. With the exception of Scenario 3, which required attending the nearest hospital (by fastest travel time) Scenario 7 minimises the % of women and men who would have to travel to the nearest of the 4 hospitals in a travel time over 30 minutes by car . With 0.02% of men and 0.5% of women having a travel time of over 30 minutes. The next best Scenario is the current status and then Scenario 1 the one 'super' hospital where 15.6% of men and 14.6% of women would have to travel over 30 minutes. As shown in Table 74 Scenario 7 has a similar average bus travel time to the current status (44.12 mins vs 44.95 mins), but much longer travel times compared to the nearest hospital (Scenario 3), which has travel times of 26.9 mins on average. Compared to the 'Super' hospital the bus travel times are much lower in Scenario 7 at 44.95 mins vs 81.8 mins.

From Chapter 3 and 4 it was identified that living in a more deprived residential location was associated with poorer health and wellbeing outcomes, so it would be good to see whether any of the scenarios are worse or better for this group of patients. As shown in Table 73 45.1% of patients living in the most deprived quintiles are < 10 minutes away from the hospital in the current scenario. Requiring patients to attend their nearest hospital (Scenario 3) increases this to 75%. All the other scenarios reduce the % of patients in the most deprived quintiles that are travelling the least (< 10 minutes). Under Scenario 4, 91% of those in the most deprived quintile would have to travel > 30 minutes to get to Harrogate District Hospital compared to 68.8% in the least deprived quintile. The hospital in Scenario 4 that maximises the number of patients travelling < 10 minutes in the most deprived quintile is Bradford. Here 17.3% of those in the most deprived quintile are travelling < 10 minutes compared to 1% of those in the least deprived

quintile. It is shown in Table 73 that scenarios that are minimising driving time do not have the same impact across all deprivation groups.

Living alone, was shown in Chapter 3 to have a negative association with ease of access. Individuals living alone were more likely to report that it was harder to access the hospital. Under the current baseline scenario 33.1% of those patients that live alone are travelling < 10 minutes and 3.9% over 30 minutes. Under Scenario 1 ('super' hospital) less patients living alone are travelling < 10 minutes to the hospital and more are travelling > 30 minutes (13.4%). Scenario 2 increases the number travelling < 10 minutes (compared to Scenario 1), but also increases the number of patients travelling > 30 minutes (compared to Scenario 1). Scenario 3 (nearest facility) results in 66.6% of those patient that live alone travelling < 10 minutes. Under Scenario 4 Chapel Allerton Hospital has the highest percentage of patients living alone with a travelling time of < 10 minutes (10.8%). Dewsbury has the lowest percentage of patients who live alone travelling > 30 minutes. Harrogate and Airedale have the highest percentage of patients living alone travelling > 30 minutes under scenario 4. Scenario 6 has a higher percentage of patients living alone travelling < 10 minutes and lower percentage of patients travelling > 30 minutes compared to scenario 1, 2, 4 and 5. Under Scenario 6, 17.7% of patients who live alone would be able to get to the hospital in < 10 minutes' drive time using the road network. This increases to 31.2% in Scenario 7. This is very close to the current state of 33.1% and reduces the percentage travelling > 30 minutes from 3.9% in the current state to 0.7% in Scenario 7.

The results in Chapter 3 showed that White British patients travelled further to the healthcare facilities that those who were classified as non-white British. How the scenarios impact on those in the non-white British category are shown in Table 73. In the current state 43.5% of non-white British Patients would have travelled < 10 minutes to have their THR or TKR operation and 3.9% > 30 minutes. Changing this to Scenario 1 results in only 8.4% now travelling < 10 minutes and 13.4% > 30 minutes, so patients would have to travel further. Under Scenario 2 more non-white British patients (than Scenario 1) are travelling < 10 minutes, but more are travelling > 30 minutes. Under Scenario 4 centralising at Bradford would have the highest percentage of non-white British patients travelling < 10 minutes, but centralising at either Chapel Allerton Hospital or Dewsbury and District hospital would result in a lower percentage of non-white British patients having to travel > 30 minutes 27.6% (Chapel Allerton Hospital) and 13.3% (Dewsbury and District). Scenario 3 (centralising at 2 hospitals) results in 19.5% of non-white British patients travelling < 10 minutes and 7.6% over 30 minutes. Whilst 29.8% of non-white British patients would have had a journey of < 10 minutes under Scenario 7.

5.3.10 Testing the scenarios to predict the impacts on health outcomes

This Chapter has so far focused on the changes in travel time and distance as a result of changing where patients access healthcare, but in terms of answering the research question the key question is:

Do these changes make any difference to patient's health outcomes?

Using the regression models developed in Chapter 3 this section predicts the change in health outcomes from changing where patients attend healthcare facilities.

Firstly, the results focus on the impact on LoS in hospital for the WY THR and TKR patients. The model predicts that under the current scenario the average LoS in hospital for a patient undergoing a THR is 5.329 days and for a TKR is it higher at 5.511 days, with non-overlapping 95% CI. Out of the 10 scenarios tested there is a predicted difference of 1.61 days in hospital between the lowest and highest THR scenarios and a predicted difference of 1.60 between the lowest and highest for TKR. In terms of cost to the NHS 1.60 days as an inpatient is around £400 per day, so £640 between the highest and lowest averages(NHS, 2018). In terms of the cost to the patient staying longer in hospital has been shown to have a negative effect on health and wellbeing. For example, Ferrando et al. (2008) found that bed rest in hospital for over 10 days can lead to 10 years of muscle decline in otherwise healthy older adults. The results show for the model where everyone is sent to Airedale hospital (scenario 4a) for their TKR this would result the longest average stays in hospital at 7.103 days compared to the currents state of 5.51 days. For THR the longest LoS would be to send everyone to Pontefract Hospital, as shown in Table 81, closely followed by Harrogate (scenario 4f). Centralising at four of the seven largest NHS hospitals increases the LoS for the THR by 0.255 and TKR by 0.296 of a day compared to the current state.

Table 78: Scenarios: Predicting Length of Stay

	THR		TKR	
	Average LoS	95% CI	Average LoS	95% CI
Sample	4,855		5,590	
Current State	5.329	5.286 – 5.372	5.511	5.475 – 5.548
Scenario 3: Nearest	4.878	4.837 – 4.921	5.501	5.470– 5.561
Scenario 4a: Airedale	6.368	6.325 – 6.410	7.103	7.06 – 7.146
Scenario 4b: Bradford	5.899	5.850 – 5.948	6.137	6.092 – 6.181
Scenario 4c: Chapel Allerton	5.485	5.424- 5.545	5.649	5.609 – 5.690
Scenario 4d: Calderdale	6.142	6.095 – 6.189	6.417	6.374 – 6.460
Scenario 4e Dewsbury	5.652	5.606 – 5.698	6,142	6.104 – 6.179
Scenario 4f: Harrogate	6.431	6.374 – 6.488	6.784	6.748 – 6.821
Scenario 4g: Pontefract	6.488	6.437 – 6.538	7.042	6.999 – 7.085
Scenario 5: 7 largest NHS	5.541	5.501 – 5.581	5.850	5.818 – 5.881
Scenario 7: Centralising at 4 hospitals	5.584	5.545 – 5.623	5.807	5.774 – 5.839

The results for predicting changes in OKS for the TKR are shown in Table 79. Using the predictive model it can be seen that the scenario whereby everyone is sent to Airedale hospital would have the lowest average positive change in OKS (13.667) as a result of the TKR compared to the current state (15.473). A difference of 2 points on average. Under the asymmetrical losses versus gains arguments made in section 3.4.3 a difference of 2 points as a 'loss' could be argued to be beyond the MCID and represent a significant difference. Limiting the number of hospitals within the WY region could have an impact on health outcomes. The scenario that limits the hospitals attended to four (scenario 7) has changes in OKS for the TKR at a similar level to the currents state (difference of 0.388). This could show that minimising the hospitals in this way is less likely to have a detrimental impact on health outcomes. Whilst still needing to assess what the impact on this might be from changing the number of patients at each hospital.

The results for THR patients focusing on the changes in OHS are shown in Table 80. As shown in the original results tables in Chapter 3 patients tend to have better health outcomes for THR than TKR. This is seen in the higher predicted change in OHS following the THR compared to Table 79 above for TKR. The difference in predicted average health change in OHS for the current state is 20.394 and the lowest change is for scenario 4f Harrogate at 18.861. Whilst again not a large difference in the average change score, but a statistically significant difference as the 95% CI do not cross. It may be possible to limit the number of hospitals (as was the case in the Manchester and London stroke centralisation examples) and achieve very similar predicted health outcomes to the current state. This of course only considers the perspective

of assumed gains from increasing the numbers treated at each hospital and minimising travel time.

Table 79 Predicting changes to OKS for patients having a TKR

	Change in OKS	95% CI
Current State	15.473	15.359 – 15.586
Scenario 3: Nearest	15.261	15.147 – 15,374
Scenario 4a: Airedale	13.667	13.551 – 13,783
Scenario 4b: Bradford	14.739	14.623 – 14.854
Scenario 4c: Chapel Allerton	15.278	15.161 – 15.394
Scenario 4d: Calderdale	14.421	14.305 – 14.538
Scenario 4e Dewsbury	15.091	14.976 – 15.206
Scenario 4f: Harrogate	13.971	13.857 – 14.086
Scenario 4g: Pontefract	13.996	13.879 – 14.114
Scenario 5: Nearest of 7 largest by car	15.134	15.021 – 15.247
Scenario 7: Centralising at 4 largest hospitals	15.085	14.972 – 15.198

Table 80 Predicting changes in OHS for patients having a THR

	Change in OHS	95% CI
Current State	20.394	20.206 - 20.503
Scenario 3: Nearest	20.348	20.199 – 29.497
Scenario 4a: Airedale	19.005	18.85 – 19.154
Scenario 4b: Bradford	19.861	19.713 – 20.010
Scenario 4c: Chapel Allerton	19.792	19.585 – 19.998
Scenario 4d: Calderdale	19.591	19.442 – 19.740
Scenario 4e Dewsbury	20.072	19.923 – 20.222
Scenario 4f: Harrogate	18.818	18.669 – 18.967
Scenario 4g: Pontefract	19.164	19.012 – 19,316
Scenario 5: Nearest of 7 largest by car	20.282	20.133 – 20.430
Scenario 7: Centralising at 4 largest hospitals	20.178	20.029 – 20.327

5.4 Estimating those individuals who would find it harder to access the hospital

As identified in this thesis there are certain groups of individuals including those who may not have access to a car that are more likely to find it harder to access the healthcare facilities. If it was possible to identify those who were more likely to find it harder to access the facilities targeted support could be put in place. This sub set of the population could also then be used as the target for where hospitals should be restructured rather than having to base the decisions on the whole population of patients. In doing this this would be directly targeting inequity.

Iteration 10 was selected from the 30, to be used in the analysis, as it had identified that lowest percentage of patients who were more likely to not have access to a car (15.5%). A summary of the population with and without a car in iteration 10 is provided in Table 81. It shows that on average individuals who were estimated to not have a car lived closer to the hospital that they attended for their THR or TKR, were more likely to attend their nearest GP, had a higher percentage of females than males, were likely to be older and live in a more highly deprived residential area. The model estimated that a much lower percentage of men than women had no access to a car. This is likely to be an underestimate, as if the man is the main driver and is the one having a THR or TKR then they would be unable to drive and so would have to use an alternative form of transport.

Table 81: summary of estimated population with and without a car

	No car/ van availability	Car availability
Total	1,547	8,924
Travel time to hospital	13.84 mins	15.06 mins
Attended the nearest Hospital	38.3%	35%
Attended the nearest GP	90%	86%
Travel time to the GP	14.78 mins	16.32 mins
Female	22%	78%
Male	11%	89%
Age (years)	72.29	67.49
Index of Multiple Deprivation	30.16	21.46
Living alone	39.8%	60.2%
Non-white British	26%	74%

5.5 Testing the scenarios using the sub set of patients estimated to find it harder to access the hospital

If an individual had access to a car or someone to drive them, then not being able to get to the appointment by bus would be less of an issue, but based on the knowledge that a large number of households in WY do not own a car this is more of an issue. Whilst Chapter 3 showed that travelling further had a negative association with patient's health outcomes for those travelling the furthest. Chapter 4 highlighted that actually it is those who find accessing healthcare the most difficult that was associated with poorer health and wellbeing outcomes, with travelling potentially further contributing to this. When targeting where to locate healthcare services it could be potentially more beneficial to base the change around minimising the impact on those who fit into these categories (those finding it harder to access the healthcare facilities). In particular individuals with mobility issues (e.g. reduced ability to walk), those without access to a car and those who would rate being able to access hospital as difficult. This section uses the subset of patients identified using the missing data analysis, as estimated as being more likely to not have access to a car when needed. It then applied this new population (subgroup no car) to the original scenarios which now have a label nc (no car) next to them. A summary of the results for the set of scenarios based on the non-car owners is provided in Table 82.

5.5.1 Scenario 1nc: One new hospital

The scenarios are repeated for this new comparison. The previous analysis looked at where you would locate a hospital if you wanted to minimise the travel times for all patients. Under this scenario it is minimising the travel times for those patients who have been estimated would not have a household car to get to the appointment. The average travel time by car would be 21.63 and range 3.63 – 48.03 mins, with journey times by bus at an average 80.56mins. Applying this location then to those who were estimated to have a car would result in an average travel time of 22.29 and range 2.61 – 50.41. On average using this method those in the car available group would have higher average travel times than those estimated to not have a car. Compared to determining this new hospital based on the complete patient population (as shown in Table 72) the average travel times by car would increase, but the average travel times by bus for those who were estimated to not have a car would decrease.

Table 82: Which scenario is best for non-Car owners? (95% CI)

	Estimated car owners	Estimated Non Car Owners		
	Car (mins)	Car (mins)	Bus (mins)	No access by bus (out of 1547)
Current State	14.76 (14.59 – 14.93	14.67 (14.24 – 15.01)	43.89 (42.73 – 45.05)	18
Scenario 1	22.29 (22.05 – 22.52)	21.63 (21.32 – 21.72)	80.56 (79.12 – 81.99)	20
Scenario 2 one existing hospital	26.56 (26.33 – 26.79)	21.74 (21.43 – 21.83)	76.56 (74.88 – 78.25)	20
Scenario 3: Nearest	9.68 (9.58 – 9.77)	9.84 (9.63 – 10.06)	27.27 (26.66 – 27.90)	13
Scenario 4a: Airedale	39.41 (39.13 – 39.67)	37.82 (37.16 – 38.47)	113.14 (110.90 – 115.39)	377
Scenario 4b: Bradford	24.36 (24.15 – 24.57)	23.00 (22.49 – 23.52)	80.22 (78.46 – 81.98)	32
Scenario 4c: Chapel Allerton	24.57 (24.36 – 24.79)	26.21 (25.71 – 26.70)	90.25 (88.36 – 92.15)	36
Scenario 4d: Calderdale	28.41 (28.17 – 28.64)	26.23 (25.66 – 26.80)	92.62 (90.44 – 94.80)	77
Scenario 4e Dewsbury	22.38 (22.20 – 22.55)	22.3 (21.86 – 22.69)	86.71 (85.17 – 88.25)	25
Scenario 4f: Harrogate	41.63 (41.39 – 41.86)	42.82 (42.26 – 43.38)	115.39 (111.79 – 113.35)	478
Scenario 4g: Pontefract	33.78 (33.51 – 34.04)	36.1 (35.49 – 36.72)	114.74 (112.38 – 117.11)	297
Scenario 5: One of 7 by car	Dewsbury and District			
Scenario 5: One of 7 by bus times			Bradford	
Scenario 6: Centralising at 2 hospitals	18.05 (17.89 – 18.21)	17.95 (17.57 – 18.33)	61.66 (61.62 – 61.71)	15
Scenario 7: Centralising at 4 hospitals	13.73 (13.60 – 13.86)	13.61 (13.31 – 13.91)	45.11 (44.06 – 46.15)	15

5.5.2 Scenario 2nc: One existing hospital that minimises travel time by car

Using the sub set of patients estimated to not have a car the one existing hospital that minimises travel time by car for non-car owners is the private hospital Spire Methley Park a different hospital to Scenario 2. The average travel time for those to Scenario 2nc is 21.63 mins (SD 9.47) and range 0.9 – 54.19 mins. Average distance 11.81 miles (SD 5.73) and range 0.3 – 30.11. If the non-car owners travelled by bus the average travel times would be 76.56mins, so faster travel times by bus than Scenario 1nc.

5.5.3 Scenario 3nc: Attending the nearest hospital

For Scenario 3 as expected attending the nearest hospital reduces overall travel times compared to the baseline scenario. In the total patient population presented in Table 72 the average travel time to the nearest hospital was 9.74. Splitting this up by those patients estimated to have a car and those estimated to not have a car (as shown in Table 82) indicate that those non car owners would have a longer average travel time by bus and car to the nearest facility compared to the car owners. The average bus travel time if everyone had travelled by bus using the patient data was 27.3mins. Under this scenario 13 patients who did not have a car would also not be able to get to the hospital by bus for the 10am appointment.

5.5.4 Scenario 4nc and Scenario 5nc: Centralising at one of the 7 largest hospitals and Scenario 5nc

Focusing on the largest of the current hospitals and focusing on scenario 4 (a-g) and Scenario 5, we can see how many of those who we have estimated to not have a car would not be able to make an appointment by 10am, as shown in table 80. It can be seen that Dewsbury Hospital has the lowest number of non-car owners who could not get to a 10am appointment, with Harrogate having the largest at 478. This differs when considering the shortest average bus travel times whereby, as shown in Table 83 Scenario 4b Braford Royal Infirmary has the shortest average bus travel times. This differs from focusing on the fastest travel times for those with a car, which would select Scenario 4e Dewsbury and District. It also differs from the results in Table 72 where the fastest average travel times by bus for the total patient population would have selected Scenario 4c (Chapel Allerton Hospital) and not Bradford, as having the quickest travel times by bus. In terms of WY patients travelling to hospital by bus there are large differences in the ease of access by bus to these different hospitals (as shown in Table 83).

Table 83: Individuals estimated to not have access to a car focusing on bus travel

Scenario	Could not get there by bus	travel times > 60 mins (number)	could not get there OR bus travel time > 1 hours
a) Airedale General Hospital	377	1,290	91.7%
b) Bradford Royal Infirmary	32	1,045	57.7%
c) Chapel Allerton Hospital	36	1,314	69.92%
d) Calderdale Royal Infirmary	77	1,427	81.12%
e) Dewsbury and District Hospital	25	1,546	81.12%
f) Harrogate District Hospital	478	1373	95.6%
g) Pontefract General Hospital	297	1365	84.3%

5.5.5 Scenario 6nc: Centralising at 2 hospitals

Minimising the travel time for non car owners resulted in Calderdale and Chapel Allerton Hospitals being selected. The average travel time by car to these hospitals for those patients who were estimated to not have access to a car was 17.95 mins and range 0.98 – 43.53, whilst making those same journeys by bus would take on average 45.11 mins with 15 patients estimated not to have a car and also not able to make a 10 am appointment by bus even if they left at 7am in the morning, as shown in Table 82. For those patients that were estimated to have access to a car these two hospitals would result in an 18.04 min average journey (SD 7.97) and range 1.07 to 50 mins. Or 9.49 mile on average journey by car range 0.23 miles to 25.49 miles.

5.5.6 Scenario 7nc: Centralising at 4 hospitals

For scenario 7nc: the location allocation method prioritising non car owners selected Pontefract, Bradford, Chapel Allerton and Calderdale as the 4 hospitals. These were the same hospitals, as selected using the total patient population. The average travel time by car for those estimated to not have a car was 13.61 minutes and by bus 45.11 mins. This resulted in a faster travel time by car than the current state (where they actually attended), but a slower travel time by bus. For the estimated car owners the travel times to the closest of these four hospitals was on average 13.73 mins.

5.5.7 Summary of scenarios for non-car owners

By identifying who we think does not have access to a car (in the absence of perfect information) we can narrow the resources put into targeting centralisation policies and target those that would find it hardest to reach the healthcare facilities to minimise the burden. Using this

method it would be possible to target the reconfiguration of healthcare services to reduce the travel time by bus or car for those who would find it harder to access the hospital, but also identify which patients who do not have a car and could not get to the hospital by bus are likely to live.

5.6 Does it matter how individuals travel?

One of the criticism of the majority of the papers in the systematic review presented in Chapter 2 was that they made the assumption that patients travelled by car to hospital. This was due to not having enough data to divide up the patients into different travelling modes and calculate travel times and distances accordingly. This is also one of the problems with the HES-PROMS dataset reported in Chapter 4, which collected no information on how patients travelled to hospital. This is a large gap our the knowledge, given that we know there is a large disparity between the travel times and distances using public transport to get to hospital and travelling by car and the journey times by the patient transport services, which make up a large proportion of travel to hospital for patient journeys. The Yorkshire Ambulance Service carried out over 886,312 patient transport service journeys alone in 2013/14 (NHS, 2018), for purposes of getting patients to and from outpatient clinics, to admitted patient treatment and treatments including dialysis and chemotherapy. Given that patients currently have a choice over where they attend this means that the Yorkshire Ambulance Services (as an example) could be required to drive patients to wherever in the country they had chosen to attend, at no cost to the patient. Whilst it was not possible to know which patients had travelled to their inpatient appointment for their THR or TKR by PTS, we know from Chapter 5 that a large number of people with a car are using the service.

In order to compare travel times by the different modes (car, bus and PTS) the PTS logs for one of the hospitals used in the WY dataset (Chapel Allerton), were analysed to see for each journey made in 2017 what was the travel time by PTS to get to the hospital. The comparable car and bus journey times were then calculated using the methods described in Chapter 3 for comparison. This dataset included all patient journeys by PTS to Chapel Allerton Hospital and was not restricted to those travelling with OA or RA (as this data was not available). The data is summarized in Table 84.

The results show that on average it is 20 minutes quicker to travel to the hospital by car than bus (using the bus schedule) and on average a further 6 minutes longer on average using the PTS. For the 48 patients who couldn't get there by bus the average travel time by PTS was 68

mins and drive time 35.62 mins. In terms of PTS this doesn't include the waiting time for the service to arrive, or the waiting time at the end of the appointment to actually get on the bus, so maybe an underestimate of the total time. This analysis using Chapel Allerton PTS data shows comparable bus and PTS travel times, but do highlight the inequalities when comparing those who can travel by car and those who travel using the PTS or public transport.

Table 84: Comparing PTS, bus and car travel times to Chapel Allerton Hospital

Journeys Sample = 9,567	Bus travel time*	Car travel time	Time on the PTS (mins)	
			Inwards	Outwards
Average	27.95 mins	7.49 mins (SD 6.82)	34.65 mins (SD 20.11)	37.78 mins (SD 22.32)
Range	3 – 174	2.02 – 49.4	1 - 273	1 - 223

* Forty-Eight journeys could not get to the hospital by bus and were excluded

5.7 Discussion

This chapter has sought to develop and apply different scenarios for reconfiguring where WY patients would access the hospital for THR and TKR and apply a method to estimate which patients are more likely to not have access to a car when needed. Some key observations that have emerged from the results are discussed next.

5.7.1 Patient vs. population data

The type of data used is critical. The analyses revealed differences in the results dependent on whether patient data or WY population data was used. One of the major discussions in Chapter 3 was of the time intensive nature of getting access to patient level data, which required high level ethical approval. The results using the patient data allowed the results to be more specific to the geographical distribution of the patients and target where the demand is located. Plus it allows the decision makers to identify key locations with limited accessibility (ability to get to the healthcare facility). As described in Chapter 3 the profile of patients who undergo THR and TKR does differ from the general population in WY, which is also shown by the Arthritis calculator results presented in Chapter 4, whereby the five different districts of WY (Leeds, Bradford, Calderdale, Wakefield and Kirklees) had differing level of population arthritis. The differences were also highlighted by the Hot spot analysis presented in Map 7, which showed that some LSOAs had higher than expected numbers of patients with THR/ and others lower than expected, so not uniformly distributed by LSOA. Also highlighted by the fact that scenarios presented in this chapter show that Scenario 6 (centralising at 2 hospitals) resulted in different hospitals being

selected (as the optimal locations that minimised road network travel time) based on the two different population groups (WY patients and WY population). However, Scenario 7 which optimised travel times across 4 hospitals in WY selected the same 4 hospitals for the patient data and population data. Does it matter? The answer depends on which type of reconfiguration is being applied. In this case study it did not make any difference in the decision for some of the scenarios, as shown by Scenario 2 (selecting one of the existing hospital) and Scenario 7 (selecting 4 hospitals). However, for Scenario 6 modelling using the patient dataset and WY population dataset resulted in selecting 2 different hospitals. In addition the WY population data underestimated how long it would take patients to get to the hospitals (both in terms of car and bus travel time). For example, under Scenario 1 the average travel time by car for the patient population using home postcodes was 20.62 minutes, but for the WY population it was 16.86 mins (difference of over 4 minutes). In this case it underestimated how long it would take, but under scenario 6 it over estimated. In reality without having access to the patient data in the first place it was not possible to know how distributed across WY the patients were to make a decision on this. Although the data from the Arthritis UK Calculator which is available now at the CCG level would have given a guide at the district level.

5.7.2 Is changing the hospital attended associated with different health outcomes?

The study tested a number of scenarios in this Chapter to assess whether changing where patients attended hospital would be associated with differences in travel times, with accessibility identified as one of the key drivers for reconfiguration. The ultimate goal was to assess whether this would ultimately be associated with changes in patients' health outcomes. Using the predictive models from Chapter 3 allowed this process to be operationalised. The results give an indication that by changing where patient's access healthcare it is possible to predict changes in LoS, OKS and OHS following a THR or TKR.

One of the limitations of the scenarios is that they limited changes to within the WY region, so limited the ultimate travel times that patients would have to travel to get to the reconfigured healthcare facility. The furthest any one patient would have to travel would be 42 miles and 79.5 mins. In the literature more extreme cases of getting patients to specialist hospitals are witnessed, for example one patient in Kerschbaumer et al. (2012) travelled 870km to the specialist hospital for brain surgery. The review in Chapter 2 did show evidence that patients are willing to travel further depending on the severity and urgency of this healthcare need. This may be less pertinent for operations such as THR or TKR where it is an elective surgery. This willingness to travel further depending on the risk is also shown by research published by

Vallejo-Torres et al. (2018) which found using discrete choice experiments that patients were willing to travel up to 75mins to reduce the risk of complications of 1%. It is with this understanding that whilst an association between travelling further and lower quality of life has been presented within this thesis, the other side of the coin is the level of care and specialist team that the patients receive in the healthcare facility that they attend. Whilst a number of the scenarios have targeted increasing the numbers of patients that any one hospital would see, which has been shown in the literature to improve health outcomes (Katz et al., 2001; Hervey et al., 2003). It has not been possible to look at all four sides of the reconfiguration process; accessibility, workforce, quality and cost, which would have needed to have been targeted using alternative research approaches than the secondary datasets that were used.

5.7.3 Restructuring where patients attend hospital

This chapter tested a number of scenarios to focus on how healthcare services could be restructured and then evaluated in terms of its impact on different groups in society. Critically Chapter 3 and Chapter 4 showed that certain groups in society have worse health and wellbeing outcomes (e.g. those living in more deprived residential location or living alone). This study allowed a comparison not only between the different scenarios in terms of how travel times varied, but also how the different groups were negatively or positively affected by these scenarios. This is a real strength of this applied method. The policy of getting patients to attend their nearest hospital reduced the number of hospitals attended and also made travel by bus and car an easier option in terms of reduced travel times. This would however, require both a change to the NHS constitution and to enforce that certain hospitals to change the volume of patients that they offered THR and TKR operations to. For example, the LGI in Leeds was the nearest hospital for a large number of the patients, but only undertook 10 THR or KR operations in the timeframe 2009 – 2012. The study showed that centralising the hospitals at 4 of the main hospitals in WY that currently do HR and KR operations resulted in lower average travel times by car and almost identical average travel times by bus to the baseline scenario (where patients currently attend –across 31 hospitals).

Focusing reconfiguration around those patients who would find accessing the healthcare facilities harder seems intuitively sound. It is worth noting that this part of the analysis was only possible using the patient data, as it required additional information about the patients (e.g. living alone, ethnic group, age, gender etc..) to be able to use the missing data methodology. The results of comparing using the patient population vs. basing the decisions on the subset estimated to not have a car did result in differing solutions. This could be a method that is

developed further. It worth remembering that these scenarios were hypothetical, but based on real patients and the hospitals that they could have attended. The method could be applied to real decisions that are currently being made.

5.7.4 How do patients travel?

Does it matter? Clearly if decisions are being made on the basis of travel times using a car as the fastest way of getting to hospital then those patients who do not travel by car are underrepresented in the travel times required to get to hospital. For example, assuming the patient population all travelled by car would have resulted in an average travel time per patient to get to their HR or KR for Scenario 1 of 20.62 (as shown in Table 74). If we assume instead that those patients estimated to not have a car (1,546) all travelled by bus and those estimated to have a car travelled by car travelled by car (the remainder) the average travel time would then be 29.62 mins. These are similar proportion of car and non car owners as report in other studies (Campbell et al., 2001)As the SEU(2003) reported a large percentage of patients have difficulties accessing healthcare facilities. Chapter 4 has shown that a large number of patients do not have access to a car when needed. As shown by the Chapel Allerton Hospital case study there is also significant differences in the travel times that different patients have to travel to get to hospital (whether by car, bus or PTS). The missing data methodology allowed the study to test a method that has not previously been applied to estimate those who would find it harder to access the hospital due to not having a car. This tried to reduce the issue of not having the perfect information. It should matter, as a critical element of the treatment process – needing to get to the appointment or in the case of the GP make the appointments as the first step in getting referred. Given that the NHS is currently paying to transport patients to their inpatient, outpatient appointments (with patients having a choice about where they can go) an evaluation of this impact of this on the costs and health outcomes is needed. For example - Do those who travel by PTS have worse outcomes?

5.7.5 What about restructuring other healthcare facilities?

Whilst the focus of this chapter has been on where to locate secondary healthcare facilities and who might be affected, the thesis has shown that actually for patients with OA or RA it is access to the GP (as the gatekeeper to the treatment) that might be the critical healthcare facilities to access. This is important given Patient Transport Service is available to get to the Hospital, but no such service exists for getting to the GP (although some GPs do do home visits). Whilst as both the Chapter 3 and 4 case studies have shown that on average individuals, as might be

imagined living closer to the GP than the distance would be needed to get to the hospital, there may still be a burden of getting there, as the distance of 1 mile to the GP might be as hard for an individual without a car as not being able to walk beyond 400m and having to travel 10 miles to the hospital by car. As shown by the GC function described in Chapter 1, restructuring that changes where patients access healthcare facilities, if it has an impact on the cost of travel, the time is takes, the levels of comfort, changes to an area unknown by the patient etc.... then it is likely to alter how easy it is to access the healthcare facility. As this thesis has shown there is some evidence that making the ease of access more difficult is associated with worse health outcomes. Policies such as longer opening hours for GPs (NHS England, 2018a), will disadvantage certain groups if the transport is not available to match the new times of the appointments (e.g. late at night or Sunday travelling), both of which have been associated with reduced public transport scheduling and night-time travel associated with increased fear of travelling (Dobbie et al., 2010)

5.8 Conclusions

This chapter has applied a number of methods to explore the potential impacts on patients and the WY population of restructuring where they access healthcare facilities. In particular it has used Location-Allocation tools to optimise locations of healthcare facilities to minimise road network travel times. Critically it has then focused on whether different groups (e.g. those in more deprived residential locations) would be negatively affected and whether this differs by scenarios and predicted whether these changes would be associated with changes in the health outcomes. One of the key issues raised in this thesis is that we do not know how these patients are travelling to the healthcare facilities. Planning healthcare services based on the quickest travel times by car is no longer a valid option given the large numbers of the population who do not have access to a car, not considering the alternative methods will put increasing demands on a cost to the NHS (the PTS to transport patients to their appointments). This chapter tested a method to estimate which patients are more likely not to have access to a car, which in the absence of perfect information could be used to target restructuring policies towards reducing the travel burden for this group in society. Using the methods applied in this chapter would allow decision makers to look at potential options and also focus in on those patients that may already find getting to the hospital harder and could target them to make it easier.

6 Chapter 6. Conclusions

6.1 Introduction

This final chapter provides a summary of the thesis, its key contributions, strengths and limitations. This is followed by a discussion of how this work could be taken forward in the future and policy implications. Finally, overall conclusions arising from the work are presented.

6.2 Summary of the thesis

The aim of this thesis as described in Chapter 1 was as follows:

To investigate the association between transport accessibility to healthcare and health inequalities for individuals with RA and OA.

To meet this aim this thesis was split into six chapters, which are summarised below.

Chapter 1 described the potential determinants of health and health inequalities. Studies in the literature have shown that patients living further away from the healthcare facilities that they need to attend had poorer health outcomes. Such findings suggest that transport accessibility to healthcare facilities is inherent in this and therefore a potential determinant of health inequalities that merits further investigation. This is particularly true, in the context of policies such as centralisation of services, whereby changes to where patients receive healthcare have the potential to result in differences in access to healthcare. Whilst it is not realistic to expect equal travel times or distances from each patient's home address to each hospital (inherently there will always be some inequalities in terms of travel times or distances) the chapter established that the impact on health from living further away should be evaluated and, where policy changes are being made, consideration should be given to reducing inequalities.

Chapter 2 presented the results of the systematic review that was designed to bring together studies that had directly considered the association between differences in travel times and distances to healthcare and potential inequalities in health outcomes (or proxy outcomes) in Global North countries. Significantly, no prior studies were identified that had considered the OA or RA disease groups, with the majority of studies instead focusing on cancer.

Chapter 3 presented the results of the first case study (WY HES-PROMS) focused on patients with OA who had had a HR or KR. It analysed , whether those living further from the GP had differences in baseline health, and whether the change in health following the operation were associated with differences in travel times and distances to the hospital.

Chapter 4 presented the results of the second case study using the participants in the ELSA data for individuals over the age of 50 years old who had either RA or OA. Using Wave 5 of the ELSA the study explored whether travel times to the healthcare facilities (GP and Hospital), were associated with inequalities in health and wellbeing. Going further than Chapter 3, it explored whether a broader definition of 'ease of access' would actually be more applicable, as living further away is only one aspect of what can make getting to the GP or hospital more difficult. This chapter identified some key predictors of individuals who would not have access to a car and highlighted problems with the extant assumption made in the majority of studies in Chapter 2 that all patients can get to the hospital directly using their own car.

Chapter 5 developed and tested a number of scenarios to assess the impact on patient travel times (by bus and car) that would result if changes were made to the locations of the THR and TKR operations. This compared both the HES-PROMS WY data (patient population) from Chapter 3 with using the WY LSOA centroid based population (WY population). An assessment was made concerning whether the different scenarios affected groups in society (e.g. gender, age, deprivation) differently, as identified from the key groups identified that are associated in the literature with health inequalities (discussed in Chapter 1). The predictors of who were more likely to not have access to a car when needed (developed in Chapter 4) were applied to the WY HES – PROMS dataset using missing data methodology to make an assessment (in the absence of perfect knowledge) about those patients that are more likely to have not travelled by car.

Chapter 6 summarises and presents together the key findings. It discusses strengths and limitations of the research, policy implications, and possible ways of taking forward the work presented in this thesis.

6.3 Summary of Research findings

To meet the main aim of this thesis the study was divided into 4 key objectives. A summary of the findings established in the individual chapters of the thesis that contribute to each of these objectives is presented below.

Objective 1: To undertake a systematic review to provide evidence concerning the association between transport accessibility to healthcare and health outcomes.

Chapter 2 presented the results of the systematic review to meet this objective. The key findings from the systematic review revealed that the majority of studies (77%) showed evidence of an association between inequalities in health outcomes (poorer health outcomes) the further a

patient lived from the healthcare facilities that they needed to attend. The majority of studies focused on cancer patients. No studies were identified that had considered patients with arthritis (OA or RA). Ninety-five percent of the studies assumed that patients would travel by car. A lack of information regarding how patients have travelled, and the underlying assumption that they can get to the hospital directly by car, has the potential to challenge the external validity of their findings and was identified as a limitation in a number of the studies.

The review highlighted some of the problems when using secondary datasets, especially where there is incomplete data, e.g. not knowing which hospital or GP that the patients attended, and simply assuming that they attended the nearest. The findings showed that it is not just about identifying patients who have to travel the furthest, as there was evidence of patients living in close proximity to the healthcare facilities often fairing the worst. For example, Kim et al. (2000) presented a nonlinear association where those living the closest and furthest away had poorer health outcomes. This was also identified in the research presented in this thesis. Using a continuous travel time measure in some cases hid the more complex association between distances and travel times and health outcomes.

The review in Chapter 2, surveyed the growing body of studies that have provided evidence of travelling further to healthcare being a determinant of health inequalities and highlighted the need to expand this evidence base particularly for disease groups that had not been considered. It is important to note that the systematic review had mixed results with a number of studies reporting no evidence of an association, five cancer studies showed as travel times increased health outcomes improved and some found a U shape association.

Objective 2: To explore and document the healthcare needs and transport accessibility to healthcare of patients with OA and RA

As described in Chapter 1 patients with OA and RA are treated in different ways and are associated with different health outcomes and demands (Figure 4 (page 32) for OA and Figure 6 (page36) for RA). The key commonality is the GP as the Gatekeeper with patients being potentially diagnosed by the GP in the case of OA patients and being referred to a specialist in the case of RA patients. Chapter 4 provides the most comprehensive comparison between individuals with RA and OA and the general population over the age of 50 years old, including information about how the individuals travelled. It found that there Were no statistically significant differences in the travel times / distances to the nearest facilities for those with OA compared to those with RA. Average travel times to the GP were 1.18 miles for OA vs 1.11 miles for RA. Average distance to the hospital was 14.5 miles for OA vs 14.54 for RA. Regarding generalising the WY case study to the rest of England, the study found that the Yorkshire and

Humberside region (including WY) had a longer travel distances to the healthcare facilities than London, but similar distances / travel times to the rest of England (outside of London). For example, the average was 1.20 miles to the nearest GP in Yorkshire and Humberside vs. 0.49 miles in London for the ELSA participants.

Interrogating the ELSA datasets showed that 82.1% of individuals with OA and 77.6% with RA stated that they had access to a car when they needed it. Whilst not everyone had access to a car when needed, the results showed that even those who stated that they had access to a car used the PTS or community transport to get to hospital. Whilst previous studies had focused on travel by car there are other stages that are critical to the journey, e.g. walking from the car park to the hospital. Chapter 4 recorded that 19% of those individuals with OA and 25% of those with RA stated that they would not be able to walk 402 metres (1/4 mile) unaided. The average walk speed test for individuals who could walk was 2.4km and hour for OA, 2.2km an hour for RA, compared to 4.8km per hour for the general ELSA population (so slower). This is particularly interesting when compared with the assumption used for how long to plan for pedestrians crossing a road at a pedestrian crossing facility which is 1.2 metres a second or 4.3km per hour DfT (1995), i.e. quicker than the average walk times for OA or RA patients. Chapter 3 which focused on patients with OA identified "access issues" with walking, but also with difficulties getting into the vehicles. As noted in Chapter 3, when presented with the results focused on travel times the study's PPI group reported that living further away made travel to health care more difficult, but what really bothered them was the level of comfort whilst travelling, issues getting into the vehicle, cramped conditions when using the PTS, and not knowing how long it would take for the PTS to take them home or an accurate time of when they would be picked up.

The results of Chapter 4 identified that a better measure of transport accessibility to healthcare might be to focus on '*ease of access'*, subsuming and including travel times to healthcare. This fits in better with the GC function introduced in Chapter 1. The results showed that living further away from the hospital (travel time), not having access to a car, having difficulty walking, being over the age of 80 years old, living alone, belonging to a non-white British ethnic group, and having fewer qualifications were all predictors of poorer *'ease of access'*. This echoes the observation from Chapter 2 that distance is not the sole determining factor and Chapter 1 that a more holistic measure is required. Key observations described in Chapter 4 showed that even those with a car have difficulties getting to hospital. Key issues with travelling include individuals travel horizons, the cost of the journey, their ability to physically undertake the journey (e.g. get

into a vehicle or walk to a bus stop) and their feelings of safety and security. This can be expressed in terms of GC.

Objective 3: *Develop statistical models to examine the associations between transport accessibility to healthcare and inequalities in health for individuals diagnosed with RA and OA. For two case studies:*

- *Case Study 1: West Yorkshire – using the linked HES-PROMS dataset*
- *Case Study 2: England – Using the ELSA dataset*

Chapters 3, 4 and 5 made the most significant contribution to this objective. In developing the cases studies one of the key process needed was to obtain ethical approval. For the HES-PROMS dataset this involved getting Section 251 approval to allow access to patient home postcode data. For the ELSA dataset approval from NatCen was required access to the grid link reference for where individuals live in order to calculate the travel times and distances to the nearest facilities. This involved a significant time commitment, but allowed the study to have access to data on actual people and more specifically the details needed on where they lived (home postcodes).The results showed that using the home postcode as the starting location compared to using the LSOA (that would not have required Section 251 approval) made a small and in most cases statistically insignificant difference to the results. A comparison was made between using the actual hospital attended and the nearest facility for the HES-PROMS data. This showed that this made a statistically *significant* difference to the travel time / distance results. Knowing the hospital attended (vs nearest hospital) had more impact than having the home postcode (vs. simply the LSOA) of the patient when calculating the travel times to the healthcare facilities.

The study focused on a range of health and wellbeing measures. Chapter 3 (using HES-PROMS data) utilised EQ-5D-3L, EQ-5D VAS, Self-Reported General Health, OHS and OKS. Chapter 4 (using ELSA data) utilised Self-Reported General Health, CASP-19 and CES_D. These required a range of statistical models to analyse the data and produced differing results by method. With the exception of Moist et al (2008), Thomas et al (2015) and Redhage et al (2013), who had focused on HRQoL none of the studies in the Chapter 2 review had applied the same health measures listed above. It was the first time they had been tested to assess the travel time/ distance association. In using these health and wellbeing measures there was an attempt to determine whether it was possible to see any statistically significant changes from measuring the association with travel time/ distance. Chapter 3 and Chapter 4 showed that it was possible to consider the association between the large range of health and wellbeing measures (not considered in the prior literature reviewed in Chapter 2) and travel distance, time and ease of

access. It should be noted that what a patient might consider as an important difference is likely to be different to a statistically significant difference. The results showed that associations between travel time / distance and changes in health and wellbeing measures whilst in some cases were statistically significant, where not large enough to meet the MCID identified from the literature for OHS/OKS and EQ-5D-3L, but that critically it identified that MCID's for loses rather than gains in health maybe very different. More work is needed in this area.

Using the ELSA dataset in Chapter 4 allowed the study to focus the models on 'ease of access' to the healthcare facilities. The models calculating access to the GP showed that as 'ease of access' decreased individuals were more likely to report being in a worse general health category (having lower CASP-19 scores) and have a higher likelihood of having 'caseworthy' depression symptoms,. The results were mixed for travel times to the GP. For Chapter 3 the models that focused on access to the GP found that as travel times increased individuals who were going to have a TKR were more likely to report being in a better general health category and having a higher baseline OKS. For access to the GP the THR patients living further away > 10 minutes vs 1 minutes from the GP were associated with a lower baseline OHS.

The model results that focused on changes to health/ wellbeing following a THR/ TKR showed that whilst including travel times as a continuous were statistically insignificant, when the travel times were split into time categories mixed results emerged. Those THR patients travelling for > 30 minutes had a negative association (statistically significantly worse) change in OHS and EQ-5D-3L than those travelling for < 10minutes. However, patients travelling between 10 to 20 and 20 to 30 minutes had a positive association (statistically significantly better change in OHS) than those travelling less than 10 minutes to the hospital. This shows similar results to some of the studies identified in Chapter 2, whereby it is those that travel the shortest and longest distances that have the poorer health outcomes, after controlling for other explanatory factors. Including 'Ease of access' to the hospital as the transport accessibility measure for the ELSA dataset (was associated with poorer self-reported health, a higher likelihood of being in a worse general health category, lower CASP19 score, higher likelihood of being classed as 'caseworthy' for depression), as individuals reported it was harder to access the hospital and GP.

Objective 4: *To test the results of the systematic review and statistical models to explore policy implications of restructuring healthcare services.*

The aim of the study was to see whether changes in transport accessibility was associated with differences in health outcomes and whether then if you changed where patients attend healthcare facilities (e.g. through a policy of reconfiguration or centralisation) this would be likely

to be associated with a change in patients' health outcomes. The results of Chapter 3 show that those who are furthest away (and to a lesser extent, those closest) from the hospitals that they attend have the worst change in health outcomes following the THR or TKR. Any policy that changes how easy it is for these individuals to access a new hospital will potentially affect this. A number of scenarios were tested to assess population groups that would be affected. The easiest way of minimising travel times to hospital was to get patients to attend their nearest hospital. However, this poses a number of issues including the allocation of a large number of patients to hospitals that previously undertook a small number of operations and goes against the current NHS policy of choice (NHS, 2017). The results of the scenarios showed that there was the potential to impact on differing relevant groups by altering where they attend healthcare facilities. The results of the predictive modelling identified that changing where some patient's accessed healthcare (increasing travel times for some) had the potential to change the average LoS in hospital and OKS/OHS health outcomes.

One of the key aspects that was identified as potentially affecting the accessibility of patients to hospital was ability to access a car to travel. The missing data methodology provided a new method for estimating car ownership drawing from the evidence from ELSA on what factors were potential predictors of car ownership. Identifying those that are more likely to require an alternative method of getting to their hospital appointment. Further work would be needed to test this methodology. In terms of evaluating where healthcare services should be reconfigured, Chapter 5 showed that it is critical to use patient data (as patients were not uniformly distributed within a geographical area) and to be able to evaluate the groups of individuals that are more likely to find it harder to access the healthcare facilities and assess changes in health. Chapter 4, for example, established that individuals with these two MSK diseases in a number of ways from the general population.

6.4 Thesis Contributions, Strengths and limitations

Meeting these objectives has led to a number of valuable and novel contributions to the research and evidence base. This was the first systematic review that had brought together key studies in global north countries that focused on travel time / distance to healthcare and health outcomes. As of April 2019 36 papers have cited this work.

This study was the first to apply for home postcode data for the HES-PROMS dataset and use this data to calculate travel times to the hospitals (both attended and nearest) and registered

GP. By applying for Section 251 approval this will now set a precedent for other researchers to have access to the same data. The recommendation would be that having LSOA is a very accurate proxy for home postcode (which is a proxy measure in itself for where the patient lives – the patients full address) and that it is not necessary to apply for home postcode.

This study was the first to apply for the home postcode (grid-link reference) for using the ELSA dataset and calculating the travel times to the healthcare facilities. It has provided evidence at a regional level that there are inequalities in access to healthcare facilities, particularly comparing London and to the rest of England. The study highlighted that it is not necessarily distance or travel time *per se* that is important, as whilst in London the travel times/ distances were shorter, but that ELSA participants in London were more likely to state that it was harder to get to both the GP and hospital.

None of the studies surveyed in Chapter 2 had calculated equivalent public transport times for the patients yet we know that not all patients have access to a car when needed. The results showed a statistically significant difference in travel times for patients if they travelled by public transport and Chapter 5 showed that these travel times are approximately equivalent to the average travel times using the PTS using the hospital in Leeds as an example. The recommendation that emerges is that we need to know more about how patients are travelling to accurately determine whether travel times have an association.

This thesis has proposed a novel missing data methodology to estimate the proportion of patients with no car as a proxy for those who might or might not travel to the hospital or GP by alternative modes of travel. The thesis showed an association between not having a car and worse health / wellbeing using the ELSA dataset. The recommendation that emerges would be for a more detailed collection of travel to healthcare data, so we know how patients have travelled. This would enable questions such as, "Does travelling by PTS lead to worse outcomes?" to be answered. Plus who should be targeted with extra help for accessing healthcare facilities.

The study used the models developed in Chapters 3 to predict the association with health outcomes (LoS and changes in OKS and OHS) following a policy of changing where patients accessed healthcare facilities. This has allowed the study to quantify the potential impacts on health from restructuring where patients access healthcare facilities. Whilst location allocation methods have been applied to various policy changes in the literature (e.g. Afshari and Peng (2014)) and using the results of linear regression for predictive modelling is commonly used in the statistical literature. The thesis has not found any examples in the literature where these two approaches have been used together, as demonstrated in this thesis.

The key strengths and limitations of the research have been discussed throughout the thesis, but some key issues are summarized here.

When the study was designed it was planned to use the ELSA-HES linked dataset. When this dataset was not available due to delays due to patient confidentiality issues the study focused on analysing the two datasets separately, as the HES-PROMS data and ELSA. This provided a key strength as it allowed a larger cohort of patients and individuals to be included (over 10,000 HES-PROMS THR and TKR patients) plus 3,298 individuals with OA or RA from the ELSA dataset. One of the limitations of using the HES-PROMS dataset was that with only 50 RA patients included who had had a TKR or THR this was too small a sample to provide valid results, so the focus for this case study reverted to OA patients.

The key strengths of the HES-PROMS dataset was that it collected baseline and follow-up data using a range of health and wellbeing measures and allowed calculations of the travel times to hospital for the TKR and THR operations using the most accurate home postcode of the patient and hospital attended. A key weakness was that it didn't include links to primary care data (other than listing the registered GP practice) and in common with the majority of the studies reviewed in Chapter 2, did not have any data on how the patients travelled to hospital. The calculated travel times did not include any allowance for weather conditions or traffic congestion, or the time spent finding a parking space and walking to the hospital, which could all impact on the actual travel time for the patients. Another limitation in the HES-PROMS dataset was that there was a large proportion of data that was missing due to patients not completing parts of the questions. This could lead to bias. A strength of the study was that it employed missing data methodology to try and take account of the potential bias from not including these patients with missing data in the analysis. The study showed similar results to other studies such as Kim et al (2000) who found a U shaped curve with those closest and furthest away having the poorer health outcomes

The key strengths of using the ELSA dataset was that it included a range of health and well-being measures for individuals that could be identified as having OA or RA. One of the limitations is that due to the study using one wave of the data and therefore unlike the HES-PROMS data not having two data points there was potential issues with using this cross sectional dataset in terms of seeing whether health changed over time. For example it is not possible to determine from one data point whether having a worse level of quality of life using the CASP19 causes individuals to find accessing the GP more difficult or whether it is the other way around (i.e. that finding the GP harder to access causes a lower CASP19). This could be partly solved in the future using longitudinal analysis methods. Other limitations are that unlike the HES-PROMS dataset

information is not available on whether individuals visited the hospital or which hospital they attended, so nearest had to be used.

To look into this research areas further requires going beyond use of secondary datasets. The study has been designed to answer the research question using a range of methods including: a systematic review analysis of secondary datasets and health accessibility analysis of scenarios that focused on changing where patients attended healthcare facilities. The study was designed to utilise existing secondary dataset rather than collecting primary data (accessing patients with OA or RA directly), as there were disease specific datasets accessible with both patients data (e.g. ethnic group, home postcode) and health outcomes data. In the timeframe available for the thesis this was preferred as it was the more effective way of ensuring a large sample size and having the variables to answer the research question posed. Using the secondary datasets allowed the whole population to be included in the case of the population in Chapter 3 or a stratified sample of the population in the case of the population in Chapter 4 for a given time period and covered a relevant area for this study. Alternative methods that were considered as part of the study were to collect primary data through questionnaires completed by patients and undertake detailed qualitative analysis through patient interviews and focus groups. Advantages to collecting some primary data would have been the ability to ask patients how long it actually took them to travel to the appointment (allowing for congestion/ road works / differences in the weather) and explore details of any difficulties they had in accessing the healthcare facilities. Focusing on answering the research question using interviews and focus groups would have allowed a greater exploration of some of the difficulties patients face in terms of accessing healthcare facilities, which is important and has been recommended for further research, but this approach would have been very expensive and time consuming to get a large enough and representative sample size to explore the associations with health outcomes that were the focus of this thesis.

Not having information on how patients travel is a key element that is missing from the data used in this thesis. A key strength is that this absence has been highlighted by the study and the study has proposed a potential method to estimate those who might not have access to a car for these trips. More work is needed in this area to firstly start to record how patients are travelling to hospital / the GP and secondary applying methods to estimate this where this is not available. Finally, a key strength is that this study had proposed a method that would allow future restructuring decisions to be evaluated in terms of impacts on health inequalities.

6.5 Policy Implications

There are a number of policy implications that arise out of this thesis that should be considered, which are discussed next.

It has been highlighted in this thesis that decisions impacting on patient journey to healthcare facilities sometimes fall between the gap of differing bodies: the NHS in charge of the patients within the healthcare system, the DfT responsible for the Transport Network, Local Authorities responsible for the local transport planning, bus companies responsible for running the bus system, the ambulance service for running the PTS, together with other organisations such as community transport to get patients to hospital. It is a complex system with multiple stakeholders. Added to this we don't know (with the exception of emergency ambulance trips) how the patients in the system are travelling. An ageing population is likely to put an increased strain on how patients get to hospital appointments beyond using a private car to get there, so policy should consider this complex system in more detail. An ageing population

Centralisation vs locally provided care: The study expected to see health outcomes becoming worse the further the patient travelled to the hospital or the GP, thereby implying that making patients travel further by moving away from locally provided care to centralised care would have an impact on health inequalities. What was observed was a U shaped curve with both those living closest and those living furthest away having poorer health outcomes. With an ageing population and increasing demand for healthcare more thought is needed as to where patients attend healthcare. This is particularly important for centralised vs local provision. The results of this thesis suggest that a policy of reducing the travel times for those travelling the furthest would be associated with improvements in health outcomes, but consideration also needs to be given to how those who are travelling the shortest distances (what could be classed as attending local healthcare) get to healthcare, especially those without access to a car. There is evidence of a trade-off between travelling further and health outcomes. Such analysis could consider, for example the trade-offs between 'ease of access' and the four key forces behind reconfiguration, workforce demands, cost, quality and safety. As Barret (2012) states the NHS should be including accessibility analysis as a core input to reconfiguration proposals rather than it being an add on that considers the consequences on travel time from other considerations such as change due to cost or workforce issues.

6.6 Further Research

This study was designed to develop a methodology that, whilst being applied to the two MSK groups of OA and RA, could then could be more generally applied to other disease groups. In particular, it would be possible and potentially revealing to apply this methodology to three of

the main disease groups identified in the systematic review – cancer, kidney dialysis and mental health. Currently, patients for operations and treatment for OA and RA can choose where they access this treatment (i.e. which hospital). Disease groups that do not currently have a choice over where they receive treatment in the UK NHS, are cancer, kidney dialysis, and mental health treatment (NHS, 2017). It would be important to assess whether this lack of choice and potentially longer average travel distance and increased number of hospital visits has a greater impact on health outcomes. There is some initial evidence of this from the review in Chapter 2.

One of the key findings from this study is that *'ease of access'* might be a better framework to explore the travel burden that patients experience in accessing hospital treatment (this would include the complexities involved in navigating to the healthcare facilities and the experiences of travelling). This fits better with the model of GC introduced in Chapter 1, whereby a patients transport accessibility is a function not only of the travel time to the healthcare facilities, but also the out-of-pocket costs, and other disutility's associated with travelling from A to B. One way that this could be explored further would be to go beyond the secondary datasets and undertake qualitative research, i.e. interview the patients and undertake evaluations of their travel experiences in their own words and then link this back to the secondary datasets. The PPI group findings presented in this thesis identified that issues in parking and then walking to the healthcare facility, long waiting times to access the PTS, journey times being longer than the road network time would suggest, and uncomfortable travelling conditions, were all key aspects that contributed to the *ease of access*. These issues could be better assessed using qualitative methods.

When the research study was first designed it was expected that it would be possible to use the linked ELSA-HES dataset. This dataset would have provided detailed information about individuals (e.g. how they travel and health and wellbeing). It would have also revealed the timing, location, and nature of hospital episodes. This would have allowed a more comprehensive analysis that combines the information used in Chapter 3 and 4. However, this dataset is due only to be released in the summer of 2019 (6 years later than it was first proposed). When released, it would therefore be possible to extend the work in this thesis to include this linked dataset.

6.7 Final Conclusions

In the face of increasing demand for healthcare services and a focus on how to improve health outcomes and reduce inequalities it is important that a holistic approach is employed, that considers all parts of the patient journey – the journey through the healthcare system *and the*

transport journey to healthcare. It is the latter part that is considered in this thesis. The thesis has provided evidence that the transport element of the journey should be considered when determining the overall health of the patient. Any policy that changes where patients access healthcare should be evaluated in terms of how it impacts on travel to healthcare and health outcomes and going beyond the implications to those travelling by car.

We need more evidence on how the journey *to* healthcare affects the journey through the patient care pathway.

References

Abdulkarin, A., Ellanti, P., Motterlini, N., T, F. and O'Byrne, J. 2013. Cemented versus uncemented fixation in total hip replacement: a systematic review and meta-analysis of randomized controlled trials. *Orthopedic Reviews.* 5(1).

Abou-Nassar, K.E., Kim, H.T., Blossom, J., Ho, V.T., Soiffer, R.J., Cutler, C.S., Alyea, E.P., Koreth, J., Antin, J.H. and Armand, P. 2012. The Impact of Geographic Proximity to Transplant Center on Outcomes after Allogeneic Hematopoietic Stem Cell Transplantation. *Biology of Blood and Marrow Transplantation.* 18(5), pp.708-715.

Acheson, D. 1998. *Independent Inquiry into Inequalities in Health Report.* [Online]. [Accessed 26 March 2019]. Available from: https://www.gov.uk/government/publications/independent-inquiry-into-inequalities-in-health-report

Adomaviciute, S., Soljak, M. and Watt, H. 2018. *Osteoarthritis prevelance models for small populations: OA prevalence models Technical Document.* [Online]. [Accessed 26 March 2019]. Available from: file:///C:/Users/tracec/Downloads/Imperial-OA-prevalence-models-technical-document.pdf

Afshari, H. and Peng, Q. 2014. Challenges and Solutions for Location of Healthcare Facilities. *Industrial Engineering and Management.* 3(2).

Agosti, P., Tettamanti, M., Vella, F.S., Suppressa, P., Pasina, L., Franchi, C., Nobili, A., Mannucci, P.M. and Sabbà, C. 2018. Living alone as an independent predictor of prolonged length of hospital stay and non-home discharge in older patients. *European Journal of Internal Medicine.* 57, pp.25-31.

Alamanos, Y. and Drosos, A.A. 2005. Epidemiology of adult rheumatoid arthritis. *Autoimmunity Reviews.* 4(3), pp.130-136.

Albornoz, C.R., Cohen, W.A., Razdan, S.N., Mehrara, B.J., McCarthy, C.M., Disa, J.J., Dayan, J.H., Pusic, A.L., Cordeiro, P.G. and Matros, E. 2016. The Impact of Travel Distance on Breast Reconstruction in the United States. *Plastic and Reconstructive Surgery.* 137(1), pp.12-18.

Allen, A., Amram, O., Tavakoli, H., Almeida, F.R., Hamoda, M. and Ayas, N.T. 2016. Relationship between Travel Time from Home to a Regional Sleep Apnea Clinic in British Columbia, Canada, and the Severity of Obstructive Sleep. *Annals of the American Thoracic Society.* 13(5), pp.719-723.

Allen, A., Carville, S. and McKenna, F. 2018. Diagnosis and management of rheumatoid arthritis in adults: summary of updated NICE guidance. *BMJ.* 362, pk3015.

Allen, K.D. and Golightly, Y.M. 2015. State of the evidence. *Current opinion in rheumatology.* 27(3), pp.276-283.

Anderson, A.E., Henry, K.A., Samadder, N.J., Merrill, R.M. and Kinney, A.Y. 2013. Rural vs Urban Residence Affects Risk-Appropriate Colorectal Cancer Screening. *Clinical Gastroenterology and Hepatology.* 11(5), pp.526-533.

Anderson, C. 2010 Central Limit Theorem. *The Corsini Encyclopedia of Psychology.* [Online]. John Wiley & Sons. [Accessed 09 January 2019]. Available from: https://onlinelibrary.wiley.com/doi/abs/10.1002/9780470479216.corpsy0160

Arcury, T.A., Preisser, J.S., Gesler, W.M. and Powers, J.M. 2005. Access to transportation and health care utilization in a rural region. *Journal of Rural Health.* 21(1), pp.31-38.

Arthritis Care. 2012. OA Nation: The most comprehensive UK report of people with osteoarthritis. [Online]. [Accessed 26 March 2019]. Available from: https://issuu.com/arthritiscare/docs/oa_nation_2012_report

Arthritis UK. 2017. *Musculoskeletal Calculator.* [Online]. [Accessed 13 February 2019]. Available from: https://www.arthritisresearchuk.org/arthritis-information/data-and-statistics/musculoskeletal-calculator.aspx

Athas, W., Adams-Cameron, M., Hunt, W., Amir-Fazli, A. and Key, C. 1999. Travel Distance to Radiation Therapy and Receipt of Radiotherapy Following Breast-Conserving Surgery. *Journal of the National Cancer Institute.* 92(3), pp.269-272.

Avina-Zubieta, J., Choi, H. and Sadatsafavi, M. 2008. Risk of cardiovascular mortality in patients with rheumatoid arthritis: a meta - analysis of observational studies. *Arthritis Rheum.* 59, pp.1690 - 1697.

Baade, P.D., Dasgupta, P., Aitken, J.F. and Turrell, G. 2011. Distance to the closest radiotherapy facility and survival after a diagnosis of rectal cancer in Queensland. *Medical Journal of Australia.* 195(6), pp.350-354.

Babyak, M.A. 2004. What You See May Not Be What You Get: A Brief, Nontechnical Introduction to Overfitting in Regression-Type Models. *Psychosomatic Medicine.* 66(3), pp.411-421.

Ballard, D.J., Bryant, S.C., O'Brien, P.C., Smith, D.W., Pine, M.B. and Cortese, D.A. 1994. Referral selection bias in the Medicare hospital mortality prediction model: are centers of referral for Medicare beneficiaries necessarily centers of excellence? *Health Services Research.* 28(6), pp.771-784.

Banks, I. and Baker, P. 2013. Men and primary care: improving access and outcomes. *Trends in Urology and Mens Health.* September (1).

Barratt, H. and Raine, R. 2012. Hospital service reconfiguration: The battle for hearts and minds. *BMJ (Online).* 344(7845), pp.20-22.

Barret, P. 2012. Safety, Sustainability, Accessibility – striking the right balance Reflections of a retiring Chair. [Online]. [Accessed 15 January 2019]. Available from: https://www.gov.uk/government/publications/safety-sustainability-accessibility

Barton, H. and Grant, M. 2006. A health map for the local human habitat. *The Journal for the Royal Society for the Promotion of Health.* 126(6), pp.252-253.

Basemap. 2015. Somerset Stroke Service Review. [Online]. [Accessed 26 March 2019]. Available from: http://www.basemap.co.uk/wp-content/uploads/2015/02/NHS-Somerset-Stroke-Service-Review-Final.pdf

Basques, B.A., Bitterman, A., Campbell, K.J., Haughom, B.D., Lin, J. and Lee, S. 2016. Influence of Surgeon Volume on Inpatient Complications, Cost, and Length of Stay Following Total Ankle Arthroplasty. *Foot & Ankle International.* 37(10), pp.1046-1051.

BBC. 2017. *Hospital cuts planned in most of England* [Online]. [Accessed 16 July 2018]. Available from: https://www.bbc.co.uk/news/health-39031546

Beard, D.J., Harris, K., Dawson, J., Doll, H., Murray, D.W., Carr, A.J. and Price, A.J. 2015. Meaningful changes for the Oxford hip and knee scores after joint replacement surgery. *Journal of clinical epidemiology.* 68(1), pp.73-79.

Becher, H. 1992. The concept of residual confounding in regression models and some applications. *Statistics in Medicine.* 11, pp.1747 - 1758.

Bellamy, N., Buchanan, W. and Goldsmith, C. 1988. Validation study of WOMAC: a health status instrument for measuring clinically important patient relevant outcomes

following total hip or knee arthroplasty in osteoarthritis. *Journal of Orthopedic Rheumatology.* 1, pp.95-108.

Bello, A.K., Hemmelgarn, B., Lin, M., Manns, B., Klarenbach, S., Thompson, S., James, M., Tonelli, M. and Alberta Kidney Disease, N. 2012. Impact of remote location on quality care delivery and relationships to adverse health outcomes in patients with diabetes and chronic kidney disease. *Nephrology Dialysis Transplantation.* 27(10), pp.3849-3855.

Bello, A.K., Wiebe, N., Hemmelgarn, B.R., Manns, B.J., Klarenbach, S.W., Thompson, S., Pelletier, R., Tonelli, M.A. and Alberta Kidney Dis, N. 2013. A population-based study on care and clinical outcomes in remote dwellers with heavy proteinuria. *Kidney International Supplements.* 3(2), pp.254-258.

Benson, T., Williams, D.H. and Potts, H.W.W. 2016. Performance of EQ-5D, howRu and Oxford hip & knee scores in assessing the outcome of hip and knee replacements. *BMC Health Services Research.* 16(1), p512.

Beswick, A.D., Wylde, V., Gooberman-Hill, R., Blom, A. and Dieppe, P. 2012. What proportion of patients report long-term pain after total hip or knee replacement for osteoarthritis? A systematic review of prospective studies in unselected patients. *BMJ Open.* 2(1), pe000435.

Bhaskan, K. and Smeeth, I. 2014. What is the difference between missing completely at random and missing at random? . *International Journal of Epidemiology.* 43(4), pp.1336-1339.

Binkley, J. 1999. The Lower Extremity Functional Scale (LEFS): Scale development, measurement properties, and

clinical application. *Physical Therapy.* 79, pp.371-383.

Blagojevic, M., Jinks, C., Jeffery, A. and Jordan, K.P. 2010. Risk factors for onset of osteoarthritis of the knee in older adults: a systematic review and meta-analysis. *Osteoarthritis and Cartilage.* 18(1), pp.24-33.

Blome, C. and Augustin, M. 2015. Measuring Change in Quality of Life: Bias in Prospective and Retrospective Evaluation. *Value in Health.* 18(1), pp.110-115.

Brant, R. 1990. Assessing proportionality in the proportional odds model for ordinal logistic regression. *Biometrics.* 46, pp.1171-1178.

Braschi, E., Shojania, K. and Allan, G.M. 2016. Anti-CCP: a truly helpful rheumatoid arthritis test? *Canadian family physician Medecin de famille canadien.* 62(3), pp.234-234.

Brewer, N., Pearce, N., Day, P. and Borman, B. 2012. Travel time and distance to health care only partially account for the ethnic inequalities in cervical cancer stage at diagnosis and mortality in New Zealand. *Australian and New Zealand Journal of Public Health.* 36(4), pp.335-342.

Bristow, R.E., Chang, J., Ziogas, A., Anton-Culver, H. and Vieira, V.M. 2014. Spatial analysis of adherence to treatment guidelines for advanced-stage ovarian cancer and the impact of race and socioeconomic status. *Gynecologic Oncology.* 134(1), pp.60-67.

Bristow, R.E., Chang, J., Ziogas, A., Gillen, D.L., Bai, L. and Vieira, V.M. 2015. Spatial analysis of advanced-stage ovarian cancer mortality in California. *American Journal of Obstetrics and Gynecology.* 213(1).

Browne, J., Adib, F., Brown, T. and Novicoff, W. 2013. Transfusion rates are increasing following total hip arthroplasty: risk factors and outcomes. *Journal of Arthroplasty.* 28(8), pp.34-37.

Buirs, L., Van Beers, L., Scholtes, V., Sprague, S. and Poolman, R. 2016. Predictors of physical functioning after total hip arthroplasty: a systematic revew. *BMJ Open.* 6(online).

Burmeister, B.H., Zarate, D.D., Burmeister, E.A., Harden, H.E., Colquist, S.P., Cossio, D.L., Poulsen, M.G., Collins, M., Pratt, G.R. and Walpole, E.T. 2010. Lung cancer patients in Queensland suffer delays in receiving radiation therapy - but not as a result of distance. *Internal Medicine Journal.* 40(2), pp.126-132.

Burn, E., Edwards, C., mURRAY, D.W., Silman, A., Cooper, C., Arden, N.K., Pinedo-Villanueva, R. and Prieto-Alhambra, D. 2018. Trends and determinants of length of stay and hospital reimbursement following knee and hip replacement: evidence from linked primary care and NHS hospital records from 1997 to 2014. *BMJ Open.* 8(1), ponline.

Buzza, C., Ono, S.S., Turvey, C., Wittrock, S., Noble, M., Reddy, G., Kaboli, P.J. and Reisinger, H.S. 2011. Distance is relative: unpacking a principal barrier in rural healthcare. *Journal of General Internal Medicine.* 26 Suppl 2, pp.648-654.

Campbell, D. 2018. Mental health patients still sent hundreds of miles for treatment. *The Guardian*

Campbell, N., Elliott, A. and Sharp, L. 2001. Rural and urban differences in stage at diagnosis of colorectal and lung cancers. *British Journal of Cancer.* 84(7), pp.910-914.

Campbell, N., Elliott, A., Sharp, L., Ritchie, L., Cassidy, J. and Little, J. 2000. Rural factors and survival from cancer: analysis of Scottish cancer registrations. *British Journal of Cancer.* 82(11), pp.1863-1866.

Care Quality Commission. 2018. *The independent regulator of health and social care in England.* [Online]. [Accessed 25 June 2018]. Available from: https://www.cqc.org.uk/

CASP. 2015. *Critical Appraisal Skills Programme.* [Online]. [Accessed 7 July 2015]. Available from: www.casp-uk.net/

Celaya, M.O., Berke, E.M., Onega, T.L., Gui, J., Riddle, B.L., Cherala, S.S. and Rees, J.R. 2010. Breast cancer stage at diagnosis and geographic access to mammography screening (New Hampshire, 1998-2004). *Rural & Remote Health.* 10(2), p1361.

Celaya, M.O., Rees, J.R. and J.J., G. 2006. Travel distance and season of diagnosis affect treatment choices for women with early stage breast cancer in a predominantly rural population. *Cancer causes & control : CCC.* 17(6), pp.851-856.

Chard, J., Kuczawski, M. and Van der Meulen, J. 2011. Patient outcomes in surgery: A report comparing independent sector treatment cntres and NHS providers. [Online]. [Accessed 26 January 2019]. Available from: file:///C:/Users/tracec/Downloads/Patient%20Outcomes%20in%20Surgery%20Report%202011.pdf

Charlson, M.E., Pompei, P., Ales, K. and Mackenzie, C.R. 1987. A new method of classifying prognostic comorbidity in Longitudinal studies: Development and validation. *Journal of Chronic Diseases.* 40(5), pp.373 - 383.

Charnley, J. 1972. The long-term results of low-friction arthroplasty of the hip performed as a primary intervention. *Journal of Bone & Joint Surgery - (Br).* 54, pp.61-76.

Cho, Y., Badve, S.V., Hawley, C.M., McDonald, S.P., Brown, F.G., Boudville M, N., Wiggins, K.J., Bannister, K.M., Clayton, P. and Johnson, D.W. 2012. The effects of living distantly from peritoneal dialysis units on peritonitis risk, microbiology, treatment and outcomes: a multi-centre registry study. *Bmc Nephrology.* 13.

Chou, S., Deily, M.E. and Li, S. 2014. Travel distance and health outcomes for scheduled surgery. *Medical Care.* 52(3), pp.250-257.

Cosford, P., Garrett, C. and Turner, K. 1997. Travel times and radiotherapy uptake in two English counties. *Public Health.* 111(1), pp.47-50.

Cramb, S.M., Mengersen, K.L., Turrell, G. and Baade, P.D. 2012. Spatial inequalities in colorectal and breast cancer survival: premature deaths and associated factors. *Health & place.* 18(6), pp.1412-1421.

Crawford, S.M., Sauerzapf, V., Haynes, R., Forman, D. and Jones, A.P. 2012. Social and geographical factors affecting access to treatment of colorectal cancer: a cancer registry study. *Bmj Open.* 2(2).

Crawford, S.M., Sauerzapf, V., Haynes, R., Zhao, H., Forman, D. and Jones, A.P. 2009. Social and geographical factors affecting access to treatment of lung cancer. *British Journal of Cancer.* 101(6), pp.897-901.

CRD. 2009. *CRD's Guidance for undertaking reviews in health care.* York: CRD, University of York.

Croft, P., Porcheret, M. and Peat, G. 2011. Managing osteoarthritis in primary care: the GP as public health physician and surgical gatekeeper. *British Journal of General Practice.* 61(589), pp.485 - 486.

Daskin, S. and Dean, L. 2004. Location of health care facilities. Handbook of OR/MS in Healthcare: A handbook of Methods and Applications., pp.43-76.

Davies, N.M., Dickson, M., Davey Smith, G., van den Berg, G.J. and Windmeijer, F. 2018. The causal effects of education on health outcomes in the UK Biobank. *Nature Human Behaviour.* 2(2), pp.117-125.

Dawson, J., Fitzpatrick, R., Carr, A. and Murray, D. 1996. Questionnaire on the perceptions of patients about total hip replacement. *Journal of Bone & Joint Surgery (Br).* 78(2), pp.185 - 190.

Dawson, J., Fitzpatrick, R., Carr, A. and Murray, D. 1998. Questionnaire on the perceptions of patients about total knee replacement. *Journal of Bone & Joint Surgery - (Br).* 80, pp.63-69.

Dejardin, O., Jones, A.P., Rachet, B., Morris, E., Bouvier, V., Jooste, V., Coombes, E., Forman, D., Bouvier, A.M. and Launoy, G. 2014. The influence of geographical access to health care and material deprivation on colorectal cancer survival: Evidence from France and England. *Health and Place.* 30, pp.36-44.

Delamothe, T. 2008. Founding Principles. *BMJ.* 336(7655), pp.1216 - 1218.

DeNino, W.F., Osler, T., Evans, E.G. and Forgione, P.M. 2010. Travel distance as factor in follow-up visit compliance in postlaparoscopic adjustable gastric banding population. *Surgery for Obesity & Related Diseases.* 6(6), pp.597-600.

Department for Communities and Local Government. 2011. The English Indicies of Deprivation 2010. [Online]. [Accessed 9 January 2019]. Available from: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/6320/1870718.pdf

Department of Health. 2009. *Implementation of the right to choose and information set out in the NHS Constitution.* [Online]. [Accessed 28 July 2018]. Available from: http://webarchive.nationalarchives.gov.uk/

Derksen, S. and Keselman, H.J. 1992. Backward, forward and stepwise automated subset selection algorithms: Frequency of obtaining authentic and noise variables. *British Journal of Mathematical and Statistical Psychology.* 45(2), pp.265-282.

DfT. 1995. *The Design of Pedestrian Crossings. Local Transport Note 2/95.* [Online]. [Accessed 7 July 2018]. Available from: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/330214/ltn-2-95_pedestrian-crossings.pdf

DfT. 2016. Free flow vehicle speed statistics: Great Britain 2015. [Online]. [Accessed 9 January 2019]. Available from: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/533244/free-flow-vehicle-speeds-great-britain-2015.pdf

DfT. 2017. *National Travel Survey: England 2016* [Online]. [Accessed 7 July 2018]. Available from: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/633077/national-travel-survey-2016.pdf

DfT. 2018. *National Travel Survey. Table NTS9902. Household carownership by region and rural urban classification: England 2002/02 to 2016/17.* [Online]. [Accessed 15 January 2019]. Available from: https://assets.publishing.service.gov.uk/

DH. 2014. Health Building Note 00-01 General design guidance for healthcare buildings. [Online]. [Accessed 15 March 2019]. Available from: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/316247/HBN_00-01-2.pdf

Dobbie, F., McConville, S. and Ormaston, R. 2010. *Understanding why some people do not use buses.* [Online]. [Accessed 9 January 2019]. Available from: https://www2.gov.scot/resource/doc/310263/0097941.pdf

Dolan, P. 1997. Modeling valuations for EuroQol health states. *Med Care.* 35(11), pp.1095 - 1108.

Dominick, K., Ahern, F., Gold, C. and Heller, C. 2004. Health-related quality of life among older adults with arthritis. *Journal of Health and Quality of Life Outcomes.* 2(5).

Donnelly, L. 2018. NHS brings in three month minimum waiting times despite warnings patients will suffer *The Telegraph*.

Doogal. 2016. *UK Postcodes* [Online]. [Accessed 2 March 2019]. Available from: https://www.doogal.co.uk/ukpostcodes.php

Dougados, M. 2016. Comodbidities in rheumatoid arthritis. *Current opinion in rheumatology.* 28(3), pp.282-288.

Dougados, M., Soubrier, M. and Atunez, A. 2013 Prevelance of comorbidities in rheumatic arthritis and evaluation of their monitoring: results of an international, cross-sectional study (COMORA). *Annals of the Rheumatic Diseases.*

Douw, K., Palmhoj Nielson, C. and Riis Pedersen, C. 2015. Centralising acute stroke care and moving care to the community in a Danish Health region: Challenges in implementing a stroke care reform. *Health Policy* 119(8), pp.1005-1010.

Dupont-Lucas, C., Dejardin, O., Dancourt, V., Launay, L., Launoy, G. and Guittet, L. 2011. Socio-geographical determinants of colonoscopy uptake after faecal occult blood test. *Digestive & Liver Disease.* 43(9), pp.714-720.

EDINA Digimap Ordnance Survey Service. 2016. *OS MasterMap ITN Layer.* [Online]. [Accessed 26 March 2019]. Available from: https://digimap.edina.ac.uk/

Edwards, H.B., Smith, M., Herrett, E., MacGregor, A., Blom, A. and Ben-Shlomo, Y. 2018. The Effect of Age, Sex, Area Deprivation, and Living Arrangements on Total Knee

Replacement Outcomes: A Study Involving the United Kingdom National Joint Registry Dataset. *JB & JS open access.* 3(2), pp.e0042-e0042.

Emery, P., Breedveld, F.C., Dougados, M., Kalden, J.R., Schiff, M.H. and Smolen, J.S. 2002. Early referral recommendation for newly diagnosed rheumatoid arthritis: evidence based development of a clinical guide. *Annals of the rheumatic diseases.* 61(4), pp.290-297.

Engelman, K., Hawley, D., Gazaway, R., Mosier, M., Ahluwalia, J. and Ellerbeck, E. 2002. Impact of geographic barriers on the utilization of mammograms by older rural women. *Journal of the American Geriatrics Society.* 50(1), pp.62-68.

Etzioni, D.A., Fowl, R. and Wasif, N. 2013. Distance Bias and Surgical Outcomes. *Medical Care.* 51, pp.238-244.

Working Time Directive 2004.

Evandrou, M., Falkingham, J., Feng, Z. and Vlachantoni, A. 2016. Ethnic inequalities in limiting health and self-reported health in later life revisited. *Journal of Epidemiology and Community Health.* 70(7), p653.

Evans, E.E., Wang, X.Q. and Moore, C.C. 2016. Distance from care predicts in-hospital mortality in HIV-infected patients with severe sepsis from rural and semi-rural Virginia, USA. *International Journal of Std & Aids.* 27(5), pp.370-376.

Felson, D., Lawrence, R., Dieppe, P., Hirsch, R., Helmick, C., Jordan, J., Kington, R., Lane, N., Nevitt, M., Zhang, Y., Sowers, M., Mcalindon, T., Spector, T., Poole, A., Yanovski, S., Ateshian, G., Sharma, L., Buckwalter, J., Brandt, K. and Fries, J. 2000. Osteoarthritis: new insights. Part 1: the disease and its risk factors. Annals of Internal Medicine. *Annals of Internal Medicine.* 133(8), pp.635-646.

Ferrando, A., Paddon-Jones, D., Protas, E., Lombeida, J., Ronsen, O., Kortebein, P., Wolfe, R., Conger, S., Symons, T.B. and Evans, W.J. 2008. Functional Impact of 10 Days of Bed Rest in Healthy Older Adults. *The Journals of Gerontology: Series A.* 63(10), pp.1076-1081.

Firozvi, A.A., Lee, C.H. and Hayashi, P.H. 2008. Greater travel time to a liver transplant center does not adversely affect clinical outcomes. *Liver Transplantation.* 14(1), pp.18-24.

Fitzgerald, J., Orav, E., Lee, T., Marcantonio, E., Poss, R., Goldman, L. and Mangione, C.M. 2004. Patient Quality of Life During the 12 Months Following Joint Replacement Surgery. *Arthritis & Rheumatism.* 51(1), pp.100 - 109.

Fleischman, A.N., Austin, M.S., Purtill, J.J., Parvizi, J. and Hozack, W.J. 2018. Patients Living Alone Can Be Safely Discharged Directly Home After Total Joint Arthroplasty: A Prospective Cohort Study. *JBJS.* 100(2), pp.99-106.

Forshaw, M., Gossage, J., Stephens, J., Strauss, D., Botha, A., Atkinson, S. and Mason, R. 2006. Centralisation of oesophagogatric cancer services: Can specialist units deliver? *Annals (Royal College of Physicians and Surgeons of England).* 88(6), pp.566- 570.

Forslind, K., Hafström, I., Ahlmén, M., Svensson, B. and Group, B.S. 2007. Sex: a major predictor of remission in early rheumatoid arthritis? *Annals of the rheumatic diseases.* 66(1), pp.46-52.

Fournel, I., Cottet, V., Binquet, C., Jooste, V., Bouvier, A., Faivre, J. and Bonithon-Kopp, C. 2010. Rural - Urban inequalities in colorectal adenoma detection rates in the general population. *Annals of Oncology.* 21, pvi57.

French, H.P., Galvin, R., Horgan, N. and Kenny, R. 2015. Prevalence and burden of osteoarthritis amongst older people in Ireland: findings from The Irish LongituDinal Study on Ageing (TILDA). *European Journal of Public Health.* 26(1), pp.192-198.

Fulop, N., Walters, R., Perri and Spurgeon, P. 2012. Implementing changes to hospital services: Factors influencing the process and 'results' of reconfiguration. *Health Policy.* 104(2), pp.128-135.

Gardiner, J., Bowen, S., Adomaviciute, S., Watt, H., Newson, R. and Soljak, M. 2017. Rheumatoid Arthritis prevalence models for small populations: Technical Document produced for Arthritis Research UK. [Online]. [Accessed 26 March 2019]. Available from: file:///C:/Users/tracec/Downloads/Rheumatoid-arthritis-prevalence-modelling-technical-document%20(4).pdf

Giuliani, O., Mancini, S., Puliti, D., Caranci, N., Ravaioli, A., Vattiato, R., Palumbo, M., Colamartini, A., Biggeri, A., Bucchi, L., Amadori, D. and Falcini, F. 2016. Patterns and determinants of receipt of follow-up mammography and/or clinical examination in a cohort of Italian breast cancer survivors. *Breast Cancer Research and Treatment.* 158(3), pp.543-551.

Glyn-Jones, S., Palmer, A.J.R., Agricola, R., Price, A.J., Vincent, T.L., Weinans, H. and Carr, A.J. 2015. Osteoarthritis. *The Lancet.* 386(9991), pp.376-387.

Goddard, M. and Smith, P. 1998. *Equity of access to healthcare. York: Centre for Health Economics.* [Online]. [Accessed 1 January 2019]. Available from: https://www.york.ac.uk/che/pdf/op32.pdf

Goldberg, D.S., French, B., Forde, K.A., Groeneveld, P.W., Bittermann, T., Backus, L., Halpern, S.D. and Kaplan, D.E. 2014. Association of distance from a transplant center with access to waitlist placement, receipt of liver transplantation, and survival among US veterans. *JAMA.* 311(12), pp.1234-1243.

Google.com. 2019. *Google Maps.* [Online]. [Accessed 09 January 2019]. Available from: https://www.google.com/maps

Gordon, M., Greene, M., Frumento, P., Rolfson, O., Garellick, G. and Stark, A. 2014. Age- and health-related quality of life after total hip replacement: decreasing gains in patients above 70 years of age. *Acta Orthopaedica.* 85(3), pp.244-249.

Goyal, S., Chandwani, S., Haffty, B.G. and Demissie, K. 2015. Effect of travel distance and time to radiotherapy on likelihood of receiving mastectomy. *Annals of Surgical Oncology.* 22(4), pp.1095-1101.

Gravelle, H. and Sutton, M. 2001. Inequality in the geographical distribution of general practitioners in England and Wales (1974 - 1995). *Journal of Health Services & Research Policy.* 6, pp.6 - 13.

Grundy, E. and Holt, G. 2000. Adult life experiences and health in early old age in Great Britain'. *Social Science and Medicine.* 51, pp.1061 - 1074.

Guardian, T. 2014. *NHS England Mass Centralisation.* [Online]. [Accessed 1 January 2019]. Available from: http://www.theguardian.com/society/2014/may/30/nhs-england-mass-centralisation-simon-stevens

Gunderson, C.C., Nugent, E.K., McMeekin, D.S. and Moore, K.N. 2013. Distance traveled for treatment of cervical cancer: who travels the farthest, and does it impact outcome? *International Journal of Gynecological Cancer.* 23(6), pp.1099-1103.

Haddad, A.Q., Singla, N., Gupta, N., Raj, G.V., Sagalowsky, A.I., Margulis, V. and Lotan, Y. 2015. Association of Distance to Treatment Facility on Quality and Survival Outcomes After Radical Cystectomy for Bladder Cancer. *Urology.* 85(4), pp.876-882.

Hair, J., Black, W., Babin, B. and Anderson, R. 2014. *Mulltivariate Data Analysis.* 7 ed. Harlow Pearson.

Hamilton, K. and Gourlay, M. 2002. *Missed hospital appointments and transport.* [Online]. [Accessed 26 March 2019]. Available from: https://www.kingsfund.org.uk/sites/default/files/UEL-missed-hospital-appointments-transport-Kerry-Hamilton-Marion-Gourlay-Kings-Fund-December-2002.pdf

Handley, T.E., Kay-Lambkin, F.J., Inder, K.J., Lewin, T.J., Attia, J.R., Fuller, J., Perkins, D., Coleman, C., Weaver, N. and Kelly, B.J. 2014. Self-reported contacts for mental health problems by rural residents: Predicted service needs, facilitators and barriers. *BMC Psychiatry.* 14(1).

Hanna, F., Teichtahl, A., Wluka, A., Wang, y., Urguhart, D., English, D., Giles, G. and Cicuttini, F. 2009. Women have increased rates of cartilage loss and progression of cartilage defects at the knee than men: a gender study of adults without clinical knee osteoarthritis. *Journal of Menopause.* 16(4), pp.666-670.

Hansen, W. 1959a. How accessibility shapes land use. *Journal of the American Institute of Planners.* 25(2), pp.73-76.

Hansen, W. 1959b. How accessibility shapes land use *Journal of the American Institute of Planners.* 25(2), pp.73-76.

Harris, C. and Coggon, D. 2015. Hip Osteoarthritis and Work. *Clinical Rheumatology* 29(3), pp.462-482.

Harrison, B.J. 2002. Influence of cigarette smoking on disease outcome in rheumatoid arthritis. *Current opinion in rheumatology.* 14(2), pp.93-97.

Harrogate and Rural District CCG. 2014. General Commissioning Statement – Hip and Knee athroplasty [Online]. [Accessed 9 January 2019]. Available from: http://www.harrogateandruraldistrictccg.nhs.uk/data/uploads/rss2/hip-and-knee-arthroplasty.pdf

Hartling, L., Milne, A., Hamm, M.P., Vandermeer, B., Ansari, M., Tsertsvadze, A. and Dryden, D.M. 2013. Testing the Newcastle Ottawa Scale showed low reliability between individual reviewers. *Journal of Clinical Epidemiology.* 66(9), pp.982-993.

Haynes, R. 2003. Geographical access to healthcare. In: Guilliford, M. and Morgain, M. eds. *Access to Healthcare.* London, pp.13-35.

Haynes, R. and Bentham, C. 1982. The effects of accessibility on general practitioner consultations, out-patient attendances and in-patient admissions in Norfolk, England. *Social science & medicine (1982).* 16(5), pp.561-569.

Haynes, R., Bentham, G., Lovett, A. and Gale, S. 1999. Effects of distances to hospital and GP surgery on hospital inpatient episodes, controlling for needs and provision. *Social Science & Medicine.* 49(3), pp.425-433.

Haynes, R., Jones, A.P., Sauerzapf, V. and Zhao, H. 2006. Validation of travel times to hospital estimated by GIS. *International Journal of Health Geographics.* 5(1), p40.

Haynes, R., Pearce, J. and Barnett, R. 2008. Cancer survival in New Zealand: ethnic, social and geographical inequalities. *Social Science & Medicine.* 67(6), pp.928-937.

Healy, W., Iorio, R., Clair, A., Pellegrini, V., Della Valle, C. and Berend, K. 2016. Complications of Total Hip Arthroplasty: Standardized List, Definitions, and Stratification Developed by The Hip Society. *Clinical Orthopedics and Related Research.* 474(2), pp.357-364.

Heart of England Foundation Trust. 2014 *Surgery Reconfiguration at Heart of England Foundation Trust: The Case for change* [Online]. [Accessed 20 January 2019]. Available from: https://hgs.uhb.nhs.uk/wp-content/uploads/Surgery-Reconfiguration-Pre-consultation-Case-for-Change.pdf

Heelan, K. and McKenna, D. 2011. Distance to specialist services and relationship to Breslow thickness at presentation of patients with malignant melanoma. *Journal of the American Academy of Dermatology.* 1), pAB118.

Henry, K., Boscoe, F.P., Johnson, C., Goldberg, D., Sherman, R. and Cockburn, M. 2011a. Breast cancer stage at diagnosis: is travel time important? *Journal of Community Health.* 36(6), pp.933-942.

Henry, K.A., Boscoe, F.P., Johnson, C.J., Goldberg, D.W., Sherman, R. and Cockburn, M. 2011b. Breast cancer stage at diagnosis: is travel time important? *Journal of Community Health.* 36(6), pp.933-942.

Henry, K.A., Sherman, R., Farber, S., Cockburn, M., Goldberg, D.W. and Stroup, A.M. 2013. The joint effects of census tract poverty and geographic access on late-stage breast cancer diagnosis in 10 US States. *Health & Place.* 21, pp.110-121.

Herdman, M., Gudex, C., Lloyd, A., Janssen, M., Kind, P., Parkin, D., Bonsel, G. and Badia, X. 2011. Development and preliminary testing of the new five-level version of EQ-5D (EQ-5D-5L). *Quality of Life Research.* 20(10), pp.1727 - 1736.

Hernandez -Alva, M. and Wailoo, A. 2016. ALDVMM: A command for fiting adjusted limited dependent variable mixture models to EQ-5D. *The Stata Journal.* 11, pp.1-13.

Hernandez -Alva, M., Wailoo, A. and Roberta, A. 2012. Tails from the Peak District: Adjusted Limited Dependent Variable Mixture Models of EQ5D Questionnaire Health State Utility Values. *Value in Health.* 15, pp.550-561.

Hervey, S.L., Purves, H.R., Guller, U., Toth, A.P., Vail, T.P. and Pietrobon, R. 2003. Provider volume of total knee arthroplasties and patient outcomes in the HCUP-Nationwide Inpatient Sample. *JBJS.* 85(9), pp.1775-1783.

Hillsman, E. 1984. The p-median structure as a unified linear model for location-allocation analysis *Environment and Planning A.* 16, pp.305 - 318.

Hinkle, D., Wiersma, W. and Jurs, S. 2003. *Applied Statistics for the Behavioural Sciences.* 5th Edition ed. Boston: Houghton Mifflin.

Ho, V. and Hamilton, B. 2000. Hospital Mergers and Acquisitions: Does Market Consolidation Harm Patients? *Journal of Health Economics.* 9, pp.767-791.

Hofstede, S., Gademan, M., Vliet Vlieland, P., Nelissen, P. and Marang-van de Mheen, P. 2016. Preoperative predictors for outcomes after total hip replacement in patients with osteoarthritis: a systematic review. *BMC Musculoskeletal Disorders.* 212(17).

Hollingworth, K. and Ness, A. 2012. The costs of centralisation: a systematic review of the economic impact of the centralisation of cancer services. *European Journal of Cancer Care.* 21, pp.158-168.

Holmes, J.A., Carpenter, W.R., Wu, Y., Hendrix, L.H., Peacock, S., Massing, M., Schenck, A.P., Meyer, A.M., Diao, K., Wheeler, S.B., Godley, P.A., Stitzenberg, K.B. and Chen, R.C. 2012. Impact of distance to a urologist on early diagnosis of prostate cancer among black and white patients. *Journal of Urology.* 187(3), pp.883-888.

Hoops, M., Rosenblatt, N., Hurt, C., Crenshaw, J. and Grabiner, M. 2012. Does lower extremity osteoarthritis exacerbate risk factors for falls in older adults? *Women's Health* 8(6), pp.685-698.

Huang, B., Dignan, M., Han, D. and Johnson, O. 2009. Does distance matter? Distance to mammography facilities and stage at diagnosis of breast cancer in Kentucky. *Journal of Rural Health.* 25(4), pp.366-371.

Hughes, C., Osman, C. and Woods, A., K. 1998. Relationship among performance on stair ambulation, functional reach, and timed up and go tests in older adults. *Issues on Ageing.* 21, pp.18-22.

Hunt, L., Ben-Shlomo, Y., Whitehouse, M.R., Porter, M. and Blom, A. 2017. The Main Cause of Death Following Primary Total Hip and Knee Replacement for Osteoarthritis: A Cohort Study of 26,766 Deaths Following 332,734 Hip Replacements and 29,802 Deaths Following 384,291 Knee Replacements. *Journal of Bone & Joint Surgery America.* 5(99), pp.565-575.

Hunt, S. and McEwan, T. 1980. The development of a subjective health indicator. *Sociology of Health and Illness.* 2, pp.231-246.

Hunter, J. and Shannon, G. 1985. Jarvis revisited: Distance decay in service areas of mid - 19th century asylums. *The professional Geographer.* 37(3), pp.296 - 302.

Hutchinson, A., Graco, M., Rasekaba, T., Parikh, S., Berlowitz, D. and Lim, W. 2015. Relationship between health-related quality of life, comorbidities and acute health care utilisation, in adults with chronic conditions. *Health Qual Life Outcomes.* 13(69).

Hyde, M., Wiggins, P., Higgs, P. and Blane, D. 2003. A measure of quality of life in early old age: The theory, development and properties of a needs satisfaction model (CASP-19). *Ageing and Mental Health.* 7(3).

Iacobucci, G. 2018. NHS staff shortages could reach 250 000 by 2030 without urgent action, experts warn. *BMJ.* 363, pk4831.

Independent Reconfiguration Panel. 2019. *About us.* [Online]. [Accessed 19 January 2019]. Available from: https://www.gov.uk/government/organisations/independent-reconfiguration-panel/about

Institite for Public Policy Research. 2018. *Future Transport Investment in the North. A briefing of the Governments new regional analysis of the national infrastructure and construction pipeline.* [Online]. [Accessed 7 July 2018]. Available from: https://www.ippr.org/files/2018-01/future-transport-investment-in-the-north-report-1801.pdf

Issa, S.N. and Sharma, L. 2006. Epidemiology of osteoarthritis: An update. *Current Rheumatology Reports.* 8(1), pp.7-15.

iStock. 2019. *Joint Anatomy picture* [Online]. [Accessed 09_01_2019]. Available from: www.istockphoto.com/gb

Jackson, K.L., Glasgow, R.E., Hill, B.R., Mone, M.C., Sklow, B., Scaife, C.L., Sheng, X. and Peche, W.J. 2013. Does Travel Distance Influence Length of Stay in Elective Colorectal Surgery? *Diseases of the Colon & Rectum.* 56(3), pp.367-373.

Jackson, K.L., Glasgow, R.E., Mone, M.C., Sheng, X., Mulvihill, S.J. and Scaife, C.L. 2014. Does travel distance influence length of stay in elective pancreatic surgery? *Hpb.* 16(6), pp.543-549.

Jaeschke, R., Singer, J. and Guyatt, G.H. 1989. Measurement of Health Status. Ascertaining the Minimally Clinically Important Difference. *Controlled Clinical Trials.* 10, pp.407-415.

Jennings, N., Boyle, M., Mahawar, K., Balupuri, S. and Small, P. 2013. The relationship of distance from the surgical centre on attendance and weight loss after laparoscopic gastric bypass surgery in the United Kingdom. *Clinical Obesity.* 3(6), pp.180-184.

Jethwa, K., Settergren, B., Berg, B. and Beal, J. 2013. Association between travel distance to a comprehensive cancer center and breast cancer stage, treatment, and outcomes in a rural state. *Cancer Prevention Research.* 1).

Jones, A., Haynes, R., Sauerzapf, V., Crawford, S., Zhoa, H. and Forman, D. 2008a. Travel time to hospital and treatment for breast, colon, rectum, lung, ovary and prostate cancer. *European Journal of Cancer* 44(7), pp.992-999.

Jones, A.P., Bentham, G., Harrison, B.D., Jarvis, D., Badminton, R.M. and Wareham, N.J. 1998. Accessibility and health service utilization for asthma in Norfolk, England. *Journal of Public Health Medicine.* 20(3), pp.312-317.

Jones, A.P., Bentham, G. and Horwell, C. 1999. Health service accessibility and deaths from asthma. *International Journal of Epidemiology.* 28(1), pp.101-105.

Jones, A.P., Haynes, R., Sauerzapf, V., Crawford, S.M. and Forman, D. 2010. Geographical access to healthcare in Northern England and post-mortem diagnosis of cancer. *Journal of Public Health.* 32(4), pp.532-537.

Jones, A.P., Haynes, R., Sauerzapf, V., Crawford, S.M., Zhao, H. and Forman, D. 2008b. Travel times to health care and survival from cancers in Northern England. *European Journal of Cancer.* 44(2), pp.269-274.

JÓNsson, T., Thorsteinsson, J. and Valdimarsson, H. 1998. Does smoking stimulate rheumatoid factor production in non-rheumatic individuals? *APMIS.* 106(7-12), pp.970-974.

Joseph, A.E. and Boeckh, J.L. 1981. Locational variation in mental health care utilization dependent upon diagnosis: A Canadian example. *Social Science and Medicine - Part D Medical Geography.* 15(3), pp.395-404.

Judge, A., Arden, N.K., Cooper, C., Javaid, K., Carr, A., Field, R. and Dieppe, P. 2012a. Predictors of outcomes of total knee replacement surgery. *Rheumatology* 51(10), pp.1804 - 1813.

Judge, A., Caskey, F.J., Welton, N.J., Ansell, D., Tomson, C.R., Roderick, P.J. and Ben-Shlomo, Y. 2012b. Inequalities in rates of renal replacement therapy in England: does it matter who you are or where you live? *Nephrology Dialysis Transplantation.* 27(4), pp.1598-1607.

Judge, A., Welton, N.J., Sandhu, J. and Ben-Shlomo, Y. 2010. Equity in access to total joint replacement of the hip and knee in England: cross sectional study. *British Medical Journal.* 341.

Jüni, P., Low, N., Reichenbach, S., Villiger, P.M., Williams, S. and Dieppe, P.A. 2010. Gender inequity in the provision of care for hip disease: population-based cross-sectional study. *Osteoarthritis and Cartilage.* 18(5), pp.640-645.

Kadam, U.T., Jordan, K. and Croft, P.R. 2004. Clinical comorbidity in patients with osteoarthritis: a case-control study of general practice consulters in England and Wales. *Annals of the Rheumatic Diseases.* 63(4), p408.

Kahneman, D. and Tversky, A. 1979. A prospect theory: An analysis of decision under risk. *Econometrica* 47, pp.263-292.

Katz, J.N., Losina, E., Barrett, J., Phillips, C.B., Mahomed, N.N., Lew, R.A., Guadagnoli, E., Harris, W.H., Poss, R. and Baron, J.A. 2001. Association between hospital and surgeon procedure volume and outcomes of total hip replacement in the United States Medicare population. *Jbjs.* 83(11), pp.1622-1629.

Kawachi, I., Subramanian, S. and Almeida-Filho, N. 2002. A glossary for health inequalities. *Journal of Epidemiology & Community Health* 56(6), pp.647-652.

Kelly, C., Hulme, C., Farragher, T. and Clarke, G. 2014. *Protocol - Do differences in travel time or distance to healthcare for adults in global north countries impact on health outcomes?* [Online]. [Accessed 1 January 2019]. Available from: http://www.crd.york.ac.uk/PROSPEROFILES/15162_PROTOCOL_20150125.pdf

Kelly, C., Hulme, C., Farragher, T. and Clarke, G. 2016. Are differences in travel time or distance to healthcare for adults in global north countries associated with an impact on health outcomes? A systematic review. *bmj open.* 12(11).

Kerschbaumer, J., Freyschlag, C.F., Bauer, R., Obwegeser, A.A., Schubert, G.A., Thome, C. and Seiz, M. 2012. Distance to the neurooncological center: a negative prognostic factor in patients with glioblastoma multiforme. An epidemiological study. *Anticancer Research.* 32(12), pp.5515-5519.

Khan, A. 1992. An integrated approach to measuring potential spatial access to healthcare services. *Socio-Economic Planning Sciences.* 26, pp.275-287.

Khera, N., Gooley, T., Flowers, M.E.D., Sandmaier, B.M., Loberiza, F., Lee, S.J. and Appelbaum, F. 2016. Association of Distance from Transplantation Center and Place of Residence on Outcomes after Allogeneic Hematopoietic Cell Transplantation. *Biology of Blood and Marrow Transplantation.* 22(7), pp.1319-1323.

Kim, C., Nevitt, M.C., Niu, J., Clancy, M.M., Lane, N.E., Link, T.M., Vlad, S., Tolstykh, I., Jungmann, P.M., Felson, D.T. and Guermazi, A. 2015. Association of hip pain with radiographic evidence of hip osteoarthritis: diagnostic test study. *BMJ.* 351, ph5983.

Kim, Y.E., Gatrell, A.C. and Francis, B.J. 2000. The geography of survival after surgery for colo-rectal cancer in southern England. *Social Science and Medicine.* 50(7-8), pp.1099-1107.

Ko, V., Naylor, J., Harris, I.A., Crosbie, J. and Yeo, A.E.T. 2013. The six-minute walk test is an excellent predictor of functional ambulation after total knee arthroplasty. *BMC Musculoskeletal Disorders.* 14(145).

Lake, I.R., Jones, N.R., Bradshaw, L. and Abubakar, I. 2011. Effects of distance to treatment centre and case load upon tuberculosis treatment completion. *European Respiratory Journal.* 38(5), pp.1223-1225.

Lamont, E.B., Hayreh, D., Pickett, K.E., Dignam, J.J., List, M.A., Stenson, K.M., Haraf, D.J., Brockstein, B.E., Sellergren, S.A. and Vokes, E.E. 2003. Is patient travel distance associated with survival on phase II clinical trials in oncology? *Journal of the National Cancer Institute.* 95(18), pp.1370-1375.

Lankila, T., Nayha, S., Rautio, A., Rusanen, J., Taanila, A. and Koiranen, M. 2016. Is geographical distance a barrier in the use of public primary health services among rural and urban young adults? Experience from Northern Finland. *Public Health.* 131, pp.82-91.

Lara, M.D., Baker, M.T., Larson, C.J., Mathiason, M.A., Lambert, P.J. and Kothari, S.N. 2005. Travel distance, age, and sex as factors in follow-up visit compliance in the post-gastric bypass population. *Surgery for Obesity & Related Diseases.* 1(1), pp.17-21.

Lard, L.R., Visser, H., Speyer, I., vander Horst-Bruinsma, I.E., Zwinderman, A.H., Breedveld, F.C. and Hazes, J.M.W. 2001. Early versus delayed treatment in patients with recent-onset rheumatoid arthritis: comparison of two cohorts who received different treatment strategies. *The American Journal of Medicine.* 111(6), pp.446-451.

Lavergne, M.R., Johnston, G.M., Gao, J., Dummer, T.J. and Rheaume, D.E. 2011. Variation in the use of palliative radiotherapy at end of life: examining demographic, clinical, health service, and geographic factors in a population-based study. *Palliative Medicine.* 25(2), pp.101-110.

Leese, G.P., Feng, Z., Leese, R.M., Dibben, C. and Emslie-Smith, A. 2013. Impact of health-care accessibility and social deprivation on diabetes related foot disease. *Diabetic Medicine.* 30(4), pp.484-490.

Lenguerrand, E., Whitehouse, M.R., Beswick, A., Toms, A., Porter, M. and Blom, A. 2017. Description of the rates, trends and surgical burden associated with revision for

prosthetic joint infection following primary and revision knee replacements in England and Wales: an analysis of the National Joint Registry for England, Wales, Northern Ireland and the Isle of Man. *bmjopen.* 7(online).

Lenhard Jr, R.E., Enterline, J.P., Crowley, J. and Ho, G.Y. 1987. The effects of distance from primary treatment centers on survival among patients with multiple myeloma. *Journal of clinical oncology : official journal of the American Society of Clinical Oncology.* 5(10), pp.1640-1645.

Lin, C.C., Bruinooge, S.S., Kirkwood, M.K., Olsen, C., Jemal, A., Bajorin, D., Giordana, S.H., Goldstein, M., Guadagnolo, B.A., Kosty, M., Hopkins, S., Yu, J.B., Arnone, A., Hanley, A., Stevens, S. and Hershman, D.I. 2015. Association Between Geographic Access to Cancer Care, Insurance, and Receipt of Chemotherapy: Geographic Distribution of Oncologists and Travel Distance. *Journal of Clinical Oncology.* 33(28), pp.3177-+.

Lipe, B.C., Lansigan, F., Gui, J. and Meehan, K. 2012. Bone marrow transplant for multiple myeloma: impact of distance from the transplant center. *Clinical Advances in Hematology & Oncology.* 10(1), pp.28-32.

Littenberg, B., Strauss, K., MacLean, C.D. and Troy, A.R. 2006. The use of insulin declines as patients live farther from their source of care: results of a survey of adults with type 2 diabetes. *BMC Public Health.* 6, p198.

London Health Observatory. 2014 *Differences in life expectancy within London* thesis.

Lou, W. and Wang, F. 2003. Measures of spatial accessibility to health care in a GIS environment: synthesis and a case study in the Chicago region. *Environment and Planning B-Planning & Design.* 30, pp.865-884.

Lovett, A., Haynes, R., Sunnenberg, G. and Gale, S. 2002. Car travel time and accessibility by bus to general practitioner services: a study using patient registers and GIS. *Social Science and Medicine.* 55, pp.97 - 111.

Luft, H.S., Robinson, J.C., Garnick, D.W., Maerki, S., C. and McPhee, S.J. 1986. The role of specialized clinical services in competition among hospitals. *Inquiry.* 23(1), pp.83-94.

Maerki, S., C., Luft, H.S. and Hunt, S.S. 1986. Selecting Categories of Patients for Regionalization. Implications of the Relationship between Volume and Outcome. *Medical Care* 24(2), pp.148-158.

Maheswaran, R., Pearson, T., Jordan, H. and Black, D. 2006. Socioeconomic deprivation, travel distance, location of service, and uptake of breast cancer screening in North Derbyshire, UK. *Journal of Epidemiology & Community Health.* 60, pp.208-212.

Malm, K., Bergman, S., Andersson, M.L.E., Bremander, A. and Larsson, I. 2017. Quality of life in patients with established rheumatoid arthritis: A phenomenographic study. *SAGE open medicine.* 5, pp.205-213.

Maltenfort, M. and Diaz-Ledezma, C. 2017. Statistics in Brief: Minimum Clinically Important Difference - Availability of Reliability Estimates. *Clinical Orthopaedics & Related Research.* 475, pp.933-946.

MapQuest. 2019. *Officicial MapQuest - Maps, Driving Directions, Live Traffic* [Online]. [Accessed 26 March 2019]. Available from: http://www.mapquest.com/

Margaretten, M., Julian, L., Katz, P. and Yelin, E. 2011. Depression in patients with rheumatoid arthritis: description, causes and mechanisms. *International journal of clinical rheumatology.* 6(6), pp.617-623.

Markin, C.J., Roessel, L.L., Lai, G.P., Turner, M. and Barst, R.J. 2011. Does geographic distance from a pulmonary hypertension center delay diagnosis and treatment? A REVEAL registry analysis. *Journal of Heart and Lung Transplantation.* 1), pS14.

Marmot, M. 2010. *Fair Society Healthy Lives (The Marmot Review).* [Online]. [Accessed 8 July 2018]. Available from: http://www.instituteofhealthequity.org/resources-reports/fair-society-healthy-lives-the-marmot-review

Marshall, D.A., Vanderby, S., Barnabe, C., MacDonald, K.V., Maxwell, C., Mosher, D., Wasylak, T., Lix, L., Enns, E., Frank, C. and Noseworthy, T. 2015. Estimating the Burden of Osteoarthritis to Plan for the Future. *Arthritis Care & Research.* 67(10), pp.1379-1386.

Martin, R. and Philippon, M. 2008. Evidence of reliability and responsiveness for the hip outcome score. *Arthroscopy.* 24(6), pp.676-682.

McCarthy, J.F., Blow, F.C., Valenstein, M., Fischer, E.P., Owen, R.R., Barry, K.L., Hudson, T.J. and Ignacio, R.V. 2007. Veterans Affairs Health System and mental health treatment retention among patients with serious mental illness: evaluating accessibility and availability barriers. *Health Services Research.* 42(3 Pt 1), pp.1042-1060.

McGrail, M., Humphreys, J. and Ward, B. 2015. Accessing doctors at times of need-measuring the distance tolerance of rural residents for health-related travel. *BMC Health Services Research.* 29(15), p212.

McGrail, M.R. and Humphreys, J.S. 2009. Measuring spatial accessibility to primary care in rural areas: iproving the effectiveness of the two-step floating catchment area method. *Applied Geography.* 29(4), pp.553-541.

McHugh, G., Campbell, M. and Luker, M. 2013. Predictors of outcomes of recovery following total hip replacement surgery. *Bone and Joint Research.* 2, pp.248-254.

McIntyre, J., Joubert, R.W.E. and Ramklass, S.S. 2014. Functional limitations and coping mechanisms of women aged 60 years and older with self-reported hand osteoarthritis. *South African Family Practice.* 56(6), pp.314-319.

McManus, S., Bebbington, P., Jenkins, R. and Brugha, T. 2016 *Adult Psychiatric Morbidity Survey: Survey of Mental Health and Wellbeing, England, 2014.*

Meden, T., St John -Larkin, C., Hermes, D. and Sommerschield, S. 2002. Relationship between travel distance and utilization of breast cancer treatment in rural northern Michigan. *JAMA - Journal of the American Medical Association.* 2287(1), p111.

Meersman, S.C., Breen, N., Pickle, L.W., Meissner, H.I. and Simon, P. 2009. Access to mammography screening in a large urban population: a multi-level analysis. *Cancer Causes & Control.* 20(8), pp.1469-1482.

Melissa. 2019. *Verify Addresses and Identities.* [Online]. [Accessed 26 March 2019]. Available from: http://www.melissadata.com/

Merrick, R. 2018. England in maternity crisis with almost half of units turning mothers away, Labour warns. *Independent*

Miller, L.M., Vercaigne, L.M., Moist, L., Lok, C.E., Tangri, N., Komenda, P., Rigatto, C., Mojica, J. and Sood, M.M. 2014. The association between geographic proximity to a dialysis facility and use of dialysis catheters. *Bmc Nephrology.* 15.

Moist, L.M., Bragg-Gresham, J.L., Pisoni, R.L., Saran, R., Akiba, T., Jacobson, S.H., Fukuhara, S., Mapes, D.L., Rayner, H.C., Saito, A. and Port, F.K. 2008. Travel time to dialysis as a predictor of health-related quality of life, adherence, and mortality: the Dialysis Outcomes and Practice Patterns Study (DOPPS). *American Journal of Kidney Diseases.* 51(4), pp.641-650.

Monnet, E., Ramee, C., Minello, A., jOOSTE, V., Carel, D. and Martino, D. 2008. Socioeconomic context, distance to primary care and detection of hepatitis C: a French population-based study. *Social Science and Medicine.* 66(5), pp.1046 - 1056.

Morris, S., Hunter, R.M., Ramsay, A.I.G., Boaden, R., McKevitt, C., Perry, C., Pursani, N., Rudd, A.G., Schwamm, L.H., Turner, S.J., Tyrrell, P.J., Wolfe, C.D.A. and Fulop, N.J. 2014. Impact of centralising acute stroke services in English metropolitan areas on mortality and length of hospital stay: difference-in-differences analysis. *BMJ.* 349.

Morris, S., Ramsay, A.I.G., Boaden, R.J., Hunter, R.M., McKevitt, C., Paley, L., Perry, C., Rudd, A.G., Turner, S.J., Tyrrell, P.J., Wolfe, C.D.A. and Fulop, N.J. 2019. Impact and sustainability of centralising acute stroke services in English metropolitan areas: retrospective analysis of hospital episode statistics and stroke national audit data. *BMJ.* 364, pl1.

Murray, D.W., Fitzpatrick, R., Rogers, K., Pandit, H., Beard, D.J., Carr, A.J. and Dawson, J. 2007. The use of the Oxford hip and knee scores. *The Journal of Bone and Joint Surgery. British volume.* 89-B(8), pp.1010-1014.

NAACCR. 2019. *NAACCR Shortest Path Finder Tool.* [Online]. [Accessed 26 March 2019]. Available from: https://www.naaccr.org/shortest-path-finder/

NatCen. 2014. *English Longitudinal Study of Ageing: Wave six interview questionnaire 2012 - 2013.* [Online]. [Accessed 08_07_2018]. Available from: file:///C:/Users/tracec/Desktop/main_questionnaire.pdf

National Joint Registry. 2017. *Summary Annual Statistics.* [Online]. [Accessed 7 August 2018]. Available from: http://www.njrcentre.org.uk/njrcentre/Healthcareproviders/Accessingthedata/StatsOnline/NJRStatsOnline/tabid/179/Default.aspx

Nattinger, A.B., Kneusel, R., Hoffman, R. and Gilligan, M. 2001. Relationship of distance from a radiotherapy facility and initial breast cancer treatment. *Journal of the National Cancer Institute.* 93(17).

Nazroo, J. 2014. Ethnic inequalities in health: addressing a significant gap in current evidence and policy. [Online]. [Accessed 26 March 2019]. Available from: https://www.thebritishacademy.ac.uk

Networks, Y.a.H.S.C. 2016. Hyper Acute Stroke Services Yorkshire and the Humber 'Blueprint' for Yorkshire and the Humber Clinical Commissioning groups [Online]. [Accessed 20 January 2019]. Available from: https://smybndccgs.nhs.uk/application/files/8014/8300/8726/Yorkshire_and_Humber_blueprint_for_HASS_for_CCGs.pdf

NEXUS. 2018. *Older People - bus concessions.* [Online]. [Accessed 18 August 2018]. Available from: https://nexus.org.uk/concessions/older-people

National Health Service Act 2006 2006. London:

NHS. 2017. *NHS Choices.* [Online]. [Accessed 14 August 2017]. Available from: www.nhs.uk/

NHS. 2018. *NHS Yorkshire Ambulance Service - Patient Transport Services (PTS).* [Online]. [Accessed 16 August 2018]. Available from: http://www.yas.nhs.uk/OurServices/patienttransportservice.html

NHS. 2018 *Reference Costs* [Online]. [Accessed 10 January 2019]. Available from: https://improvement.nhs.uk/resources/reference-costs/

NHS. 2019a. *Can I choose where to receieve treatment?* [Online]. [Accessed 15 January 2019]. Available from: https://www.nhs.uk/common-health-questions/nhs-services-and-treatments/can-i-choose-where-to-receive-treatment/

NHS. 2019b. Diagnosis: Rheumatoid Arthritis. [Online]. [Accessed 9 January 2019]. Available from: https://www.nhs.uk/conditions/rheumatoid-arthritis/diagnosis/

NHS Digital. 2016a. *GP and GP practice related data - EPRACCUR.* [Online]. [Accessed 26 March 2019]. Available from: https://digital.nhs.uk/organisation-data-service/data-downloads/gp-data

NHS Digital. 2016b. Organisation Data Service Standards Repository [Online]. [Accessed 8 March 2018]. Available from: https://digital.nhs.uk/organisation-data-service/data-downloads/gp-data.

NHS Digital. 2017 *Oragnisation Data Service.* [Online]. [Accessed 16 September 2017]. Available from: https://digital.nhs.uk/services/organisation-data-service/data-downloads

NHS Digital. 2018a. *Estimated alcohol-rellated hospital admissions* [Online]. [Accessed 9 January 2019]. Available from: https://digital.nhs.uk/data-and-information/publications/statistical/statistics-on-alcohol/2018/part-1

NHS Digital. 2018b. *General Practice Workforce, Final 30 September 2018, Experimental statistics.* [Online]. [Accessed 28 March 2019]. Available from: https://digital.nhs.uk/

NHS Digital. 2018c. *Health Survey for England* [Online]. [Accessed 17 December 2018]. Available from: https://digital.nhs.uk/data-and-information/publications/statistical/health-survey-for-england

NHS Digital. 2018d. *Statistics on Obesity, Physical Activity and Diet - England, 2018.* [Online]. [Accessed 9 January 2019]. Available from: https://digital.nhs.uk/data-and-information/publications/statistical/statistics-on-obesity-physical-activity-and-diet/statistics-on-obesity-physical-activity-and-diet-england-2018

NHS England. 2015. *Stroke Services: Configurations Decision Support Guide.* [Online]. [Accessed 19 January 2019]. Available from: https://www.england.nhs.uk/

NHS England. 2017. *Sustainability and transformation partnerships (STPs).* [Online]. [Accessed 26 March 2019]. Available from: https://www.england.nhs.uk/stps/

NHS England. 2018a. *Improving Access to General Practice.* [Online]. [Accessed 9 January 2019]. Available from: https://www.england.nhs.uk/gp/gpfv/redesign/improving-access/

NHS England. 2018b. *West Yorkshire and Harrogate STP.* [Online]. [Accessed 23 May 2018]. Available from: https://www.england.nhs.uk/systemchange/view-stps/west-yorkshire-and-harrogate/

NHS England. 2018 *Missed Appointments* [Online]. [Accessed 11 January 2019]. Available from: https://www.england.nhs.uk/

NICE. 2014a. *Osteoarthritis: care and management.* [Online]. [Accessed 7 July 2018]. Available from: https://www.nice.org.uk/guidance/cg177

NICE. 2014b. Total hip replacement and resurfacing arthroplasty for end stage arthritis of the hip. *Technology Appraisal Guidance.* [Online]. [Accessed 9 January 2019]. Available from: nice.org.uk/guidance/ta304

NICE. 2015a. Osteoarthritis. Quality Standard. [Online]. [Accessed 26 March 2019]. Available from: https://www.nice.org.uk/guidance/qs87/resources/osteoarthritis-pdf-2098913613253

NICE. 2015b. *Rheumatoid arthritis in adults: management.* [Online]. [Accessed 07_07_2018]. Available from: https://www.nice.org.uk/guidance/cg79

Nilsdotter, A. and Bremander, A. 2011. Measures of hip function and symptoms: Harris Hip Score (HHS), Hip Disability and Osteoarthritis Outcome Score (HOOS), Oxford Hip Score (OHS), Lequesne Index of Severity for Osteoarthritis of the Hip (LISOH), and American Academy of Orthopedic Surgeons (AAOS) Hip and Knee Questionnaire. *Arthritis Care Research.* 63(suppl 11), pp.S200-207.

NJR. 2010. National Joint Registry for England and Wales. 7th Annual Report: 2010. [Online]. [Accessed 9 January 2019]. Available from: http://www.njrcentre.org.uk/njrcentre/portals/0/njr%207th%20annual%20report%202010.pdf

Norman, P. 2010. Identifying change over time in small area socio-economic deprivation. *Applied Spatial Analysis and Policy.* 3(2-3), pp.107 - 138.

Onitilo, A.A., Liang, H., Stankowski, R.V., Engel, J.M., Broton, M., Doi, S.A. and Miskowiak, D.A. 2014. Geographical and seasonal barriers to mammography services and breast cancer stage at diagnosis. *Rural and Remote Health.* 14(3).

ONS. 2012. *2011 Census: Digitised Boundary Data (England and Wales).* [Online]. [Accessed 26 March 2019]. Available from: https://borders.ukdataservice.ac.uk/

ONS. 2016a. *2011 Census aggregate data. UK Data Service* [Online]. [Accessed 7 July 2018].

ONS. 2016b. *Census aggregate data. UK Data Service (Edition: June 2016.* [Online]. [Accessed 7 July 2018]. Available from: http://dx.doi.org/10.5257/census/aggregate-2011-1

ONS. 2017 *National Population Projections: 2016-based statistical bulletin.* [Online]. [Accessed 7 July 2018]. Available from: https://www.ons.gov.uk/

ONS. 2018a. *2011 LSOA population weighted centroids.* [Online]. [Accessed 7 July 2018]. Available from: http://webarchive.nationalarchives.gov.uk/20160110200251/http://www.ons.gov.uk/ons/guide-method/geography/products/census/spatial/centroids/index.html

ONS. 2018b. *Adult smoking habits in the UK: 2017.* [Online]. [Accessed 09_01_2019]. Available from: https://www.ons.gov.uk/

ONS. 2018c. *National life tables, UK: 2015 to 2017* [Online]. [Accessed 9 January 2019]. Available from: https://www.ons.gov.uk/

Oppe, M., Devlin, N. and Black, N. 2011. Comparison of the underlying constructs of the EQ-5D and Oxford Hip Score: implications for mapping. *Value Health.* 14(6), pp.884-891.

Palazzo, C., Nguyen, C., Lefevre-Colau, M.-M., Rannou, F. and Poiraudeau, S. 2016. Risk factors and burden of osteoarthritis. *Annals of Physical and Rehabilitation Medicine.* 59(3), pp.134-138.

Palmer, K. 2011. *Reconfiiguring hospital services: Lessons from South East London.* [Online]. [Accessed 15 January 2019]. Available from: https://www.kingsfund.org.uk/sites/default/files/Reconfiguring-hospital-services-lessons-South-East-London-Kings-Fund-March-2011_0.pdf

Panagopoulou, P., Gogas, H., Dessypris, N., Maniadakis, N., Fountzilas, G. and Petridou, E.T. 2012. Survival from breast cancer in relation to access to tertiary healthcare, body mass index, tumor characteristics and treatment: a Hellenic Cooperative Oncology Group (HeCOG) study. *European Journal of Epidemiology.* 27(11), pp.857-866.

Parkin, D., Devlin, N. and Feng, Y. 2016. What Determines the Shape of an EQ-5D Index Distribution? *Medicine Decision Making.* 36(8), pp.941-951.

Parsons, C., Clynes, M., Syddall, H., Jagannarth, D., Litwic, A. and Pas, S.D. 2015. How well do radiographic, clinical and self-reported diagnoses of knee osteoarthritis agree? Findings from the Hertfordshire cohort study

Springerplus. 15, pp.4-177.

Peersman, G., Laskin, R., Davis, J. and Peterson, M. 2001. Infection in total knee replacement: a retrospective review of 6489 total knee replacements. *Clinical Orthopaedics & Related Research.* 392, pp.15-23.

Podmore, B., Hutchings, A., van der Meulen, J., Aggarwal, A. and Konan, S. 2018. Impact of comorbid conditions on outcomes of hip and knee replacement surgery: a systematic review and meta-analysis. *BMJ Open.* 8(7), pe021784.

Podsiadlo, D. and Richardson, S. 1991. The timed "Up & Go": a test of basic functional mobility for frail elderly persons. *Journal of American Geriatric Society.* 39(2), pp.142-148.

Potvin, A., Syndulko, K., Tourtellotte, W., Lemmon, J. and Potvin, J. 1980. Human neurologic function and the aging process. *Journal of American Geriatric Society.* 28, pp.1-9.

Powers, M. 1964. *Footprints in the sand.* [Online]. [Accessed 26 March 2019]. Available from: https://www.onlythebible.com/Poems/Footprints-in-the-Sand-Poem.html

Prieto-Alhambra, D., Nogues, X., Javaid, M.K., Wyman, A., Arden, N.K., Azagra, R., Cooper, C., Adachi, J.D., Boonen, S., Chapurlat, R.D., Compston, J.E., Gehlbach, S.H., Greenspan, S.L., Hooven, F.H., Netelenbos, J.C., Pfeilschifter, J., Rossini, M., Sambrook, P.N., Silverman, S., Siris, E.S., Watts, N.B. and Díez-Pérez, A. 2013. An increased rate of falling leads to a rise in fracture risk in postmenopausal women with self-reported osteoarthritis: a prospective multinational cohort study (GLOW). *Annals of the Rheumatic Diseases.* 72(6), pp.911-917.

Prue, D.M., Keane, T.M., Cornell, J.E. and Foy, D.W. 1979. An analysis of distance variables that affect aftercare attendance. *Community Mental Health Journal.* 15(2), pp.149-154.

Punglia, R., Weeks, J., Neville, B. and Earle, C. 2006. Effect of distance to radiation treatment facility on use of radiation therapy after mastectomy in elderly women. *International Journal of Radiation Oncology Biology Physics.* 66(1), pp.56-63.

Putnam, R. 2000. *Bowling Alone: The Collapse and Revival of American Community.* New York: Simon & Schuster.

Radloff, L. 1977. The CES-D Scale: A self reported Depression Scale for Research in the General Population *Applied Psychological Measurement.* 1(3), pp.385-401.

Ragon, B.K., Clifton, C., Chen, H., Savani, B.N., Engelhardt, B.G., Kassim, A.A., Vaughan, L.A., Lucid, C. and Jagasia, M. 2014. Geographic Distance Is Not Associated with Inferior Outcome When Using Long-Term Transplant Clinic Strategy. *Biology of Blood and Marrow Transplantation.* 20(1), pp.53-57.

Rahman, S. and Smith, D. 2000. Use of Location-Allocation Models in Health Service Development Planning in Developing Nations. *European Journal of Operational Research.* 123, pp.437-452.

Ravi, B., Jenkinson, R., Austin, P.C., Croxford, R., Wasserstein, D., Escott, B., Paterson, J.M., Kreder, H. and Hawker, G.A. 2014. Relation between surgeon volume and risk of complications after total hip arthroplasty: propensity score matched cohort study. *BMJ : British Medical Journal.* 348, pg3284.

Redhage, L.D., Harms, K., Moore, D.E., Pinson, C.W. and Feurer, I.D. 2013. Closer proximity to the transplant center is associated with better physical health-related quality of life after liver transplantation. *Hpb.* 15, pp.65-66.

Roach, K. and Miles, T. 1991. Normal Hip and Knee Active Range of Motion: The Relationship to Age. *Physical Therapy.* 71(9), pp.656 - 665.

Rodkey, S.M., Hobbs, R.E., Goormastic, M. and Young, J.B. 1997. Does distance between home and transplantation center adversely affect patient outcomes after heart transplantation? *Journal of Heart and Lung Transplantation.* 16(5), pp.496-503.

ROOS, E., Roos, H., Lochmander, L., Ekdahl, C. and Beynnon, B. 1998. Knee Injury and Osteoarthritis Outcome Score (KOOS) – Development of a Self-Administered Outcome Measure. *Jorunal of Orthopedic and Sports Physical Therapy.* 78(2), pp.88-96.

Royston, P. and White, I. 2011. Multiple Imputation by Chained Equations

(MICE): Implementation in Stata. *Journal of Statistical Software.* 45(4).

Sackett, D., Richardson, W., Rosenberg, W. and Haynes, R. 1997. *Evidence -based medicine: how to practice and teach EBM. .* New York: Churchill Livingston.

Sauerzapf, V., Jones, A., Haynes, R., Crawford, S. and Forman, D. 2008. Travel time to radiotherapy and uptake of breast-conserving surgery for early stage cancer in Northern England. *Health & Place.* 14(3), pp.424-433.

Schroen, A., Brenin, D., Kelly, M., Knaus, W. and Slingluff, C. 2005. Impact of patient distance to radiation therapy on mastectomy use in early-stage breast cancer patients. *Journal of Clinical Oncology.* 23(28), pp.7074-7080.

Schroen, A. and Lohr, M. 2009. Travel Distance to Mammography and the Early Detection of Breast Cancer. *The Breast Journal.* 15(2), pp.216-217.

Scoggins, J.F., Ramsey, S.D., Jackson, J.C. and Taylor, V.M. 2010. Cost effectiveness of a program to promote screening for cervical cancer in the Vietnamese-American population. *Asian Pacific Journal of Cancer Prevention: Apjcp.* 11(3), pp.717-722.

Scuderi, G., Bourne, R.B., Noble, P., Benjamin, J., Lonner, J. and Scott, W. 2012. The New Knee Society Knee Scoring System. *Clinical Orthopedics and Related Research.* 470(1), pp.3 - 19.

Simons, C., Rivero-Arias, O., Yu, L. and Simon, J. 2015. Multiple Imputation to deal with missing EQ-5D-3L data: Should we imput individual domains or the actual index? *Quality of Life Research.* 24(4), pp.805-815.

Singh, D., Jaiswal, V., Sonkar, A.A., Kumar, S. and Singh, S. 2014. Randomized control trial of conventional laparoscopic versus single incision laparoscopic cholecystectomy. *Hpb.* 16, p115.

Singh, J., Schleck, C., Harmsen, W. and Lewallen, D. 2016. Validation of the Mayo Hip Score: construct validity, reliability and responsiveness to change. *BMC Musculoskeletal Disorders.* 17(39), ponline.

Sivagnanam, P. and Rhodes, M. 2010. The importance of follow-up and distance from centre in weight loss after laparoscopic adjustable gastric banding. *Surgical Endoscopy and Other Interventional Techniques.* 24(10), pp.2432-2438.

Skarsvag, K. and Wynn, R. 2004. Travel Time and the Use of Psychiatric Outpatient Clinic Services in Coastal Northern Norway [4]. *Canadian Journal of Psychiatry.* 49(2), pp.153-154.

Sköldstam, L., Hagfors, L. and Johansson, G. 2003. An experimental study of a Mediterranean diet intervention for patients with rheumatoid arthritis. *Annals of the Rheumatic Diseases.* 62(3), p208.

Small, K. and Verhoef, E. 2007. *The economics of urban transportation.* 2nd Edition ed. London Routledge.

Smith, M.C., Ben-Shlomo, Y., Dieppe, P., Beswick, A.D., Adebajo, A.O., Wilkinson, J.M. and Blom, A.W. 2017. Rates of hip and knee joint replacement amongst different ethnic groups in England: an analysis of National Joint Registry data. *Osteoarthritis and Cartilage.* 25(4), pp.448-454.

Smyth C. 2018. Jeremy Hunt promises new NHS hopsital every year in £3.5bn splurge. *The Times*

Social Exclusion Unit. 2003. *Making the connections: Final report on transport and social exclusion.* [Online]. [Accessed 7 July 2018]. Available from: http://www.carplus.org.uk/wp-content/uploads/2012/08/Making-the-Connections-Final-Report-on-Transport-and-Social-Exclusion_Social-Exclusion-Unit_2003.pdf

Stigler, S. 2008. Fisher and the 5% Level. *CHANCE.* 21(4), pp.12-12.

Stoller, J.K., Sandhaus, R.A., Turino, G., Dickson, R., Rodgers, K. and Strange, C. 2005. Delay in diagnosis of alpha1-antitrypsin deficiency: A continuing problem. *Chest.* 128(4), pp.1989-1994.

Strauss, K., MacLean, C., Troy, A. and Littenberg, B. 2006. Driving distance as a barrier to glycemic control in diabetes. *Journal of General Internal Medicine.* 21(4), pp.378-380.

Swan-Kremeier, L.A., Mitchell, J.E., Twardowski, T., Lancaster, K. and Crosby, R.D. 2005. Travel distance and attrition in outpatient eating disorders treatment. *International Journal of Eating Disorders.* 38(4), pp.367-370.

Symmons, D. 2002. Epidemiology of rheumatoid arthritis: determinants of onset, persistence and outcome. *Best Practice and Research Clinical Rheumatology.* 16(5), pp.707-722.

Symmons, D.P.M. 2003. Environmental factors and the outcome of rheumatoid arthritis. *Best Practice & Research Clinical Rheumatology.* 17(5), pp.717-727.

Teitz, M. and Bart, P. 1968. Heuristic methods for estimating the generalised vertex median of a weighted graph. *Operations Research.* 16, pp.955 - 961.

Tektonidou, M., Dasgupta, A. and M., W. 2011. Suicidal ideation among adults with arthritis: prevalence and subgroups at highest risk. Data from the 2007-2008 National Health and Nutrition Examination Survey. . *Arthritis Care and Research.* 63(9), pp.1322-1333.

Temkin, S.M., Fleming, S.A., Amrane, S., Schluterman, N. and Terplan, M. 2015. Geographic disparities amongst patients with gynecologic malignancies at an urban NCI-designated cancer center. *Gynecologic Oncology.* 137(3), pp.497-502.

Tengstrand, B., Nordmark, B., Wretenberg, P. and Stark, A. 2008. The foot: still the most important reason for walking incapacity in rheumatoid arthritis: Distribution of symptomatic joints in 1,000 RA patients AU - Grondal, Lollo. *Acta Orthopaedica.* 79(2), pp.257-261.

Thabut, G., Munson, J., Haynes, K., Harhay, M.O., Christie, J.D. and Halpern, S.D. 2012. Geographic Disparities in Access to Lung Transplantation Before and After Implementation of the Lung Allocation Score. *American Journal of Transplantation.* 12(11), pp.3085-3093.

The Cochrane Collaboration. 2011. *Cochrane Handbook for Systematic Reviews of Interventions.* [Online]. [Accessed 26 March 2019]. Available from: http://handbook-5-1.cochrane.org/chapter_9/9_1_4_when_not_to_use_meta_analysis_in_a_review.htm

The EuroQol Group. 1990. EuroQol—a new facility for the measurement of health related quality of life. Health Policy 1990;16:199–208. . *Health Policy & Planning.* 16, pp.199 - 208.

The King's Fund. 2018. *Trusts in deficit.* [Online]. [Accessed 15 January 2019]. Available from: https://www.kingsfund.org.uk/projects/nhs-in-a-nutshell/trusts-deficit

Theiss, M., Ellison, M., Tea, C., Warner, J.J., Silver, R. and Murphy, V. 2011. The connection between strong social support and joint replacement outcomes. *Journal of Orthopedics.* 18(34), p357.

Thomas, A.A., Gallagher, P., O'Ceilleachair, A., Pearce, A., Sharp, L. and Molcho, M. 2015. Distance from treating hospital and colorectal cancer survivors' quality of life: a gendered analysis. *Supportive care in cancer : official journal of the Multinational Association of Supportive Care in Cancer.* 23(3), pp.741-751.

Thompson, S., Bello, A., Wiebe, N., Manns, B., Hemmelgarn, B., Klarenbach, S., Pelletier, R., Tonelli, M. and Alberta Kidney Disease, N. 2013. Quality-of-care indicators among remote-dwelling hemodialysis patients: a cohort study. *American Journal of Kidney Diseases.* 62(2), pp.295-303.

Thompson, S., Gill, J., Wang, X., Padwal, R., Pelletier, R., Bello, A., Klarenbach, S. and Tonelli, M. 2012. Higher mortality among remote compared to rural or urban dwelling hemodialysis patients in the United States. *Kidney International.* 82(3), pp.352-359.

Timmins, K. and Edwards, K. 2016. *Validation of Spatial Microsimulation Models: a Proposal to Adopt the Bland-Altman Method.*

TNDS. 2016. *Traveline National Dataset.* [Online]. [Accessed 15_09_2016]. Available from: ftp.tnds.basemap.co.uk

Tobin, J. 1958. Estimation of relationships for limited dependent variables. *Econometrica.* 26, pp.24-36.

Tonelli, M., Hemmelgarn, B., Culleton, B., Klarenbach, S., Gill, J.S., Wiebe, N., Manns, B. and Alberta Kidney Disease, N. 2007a. Mortality of Canadians treated by peritoneal dialysis in remote locations. *Kidney International.* 72(8), pp.1023-1028.

Tonelli, M., Klarenbach, S., Manns, B., Culleton, B., Hemmelgarn, B., Bertazzon, S., Wiebe, N., Gill, J.S. and Alberta Kidney Dis, N. 2006. Residence location and likelihood of kidney transplantation. *Canadian Medical Association Journal.* 175(5), pp.478-482.

Tonelli, M., Manns, B., Culleton, B., Klarenbach, S., Hemmelgarn, B., Wiebe, N., Gill, J.S. and Alberta Kidney Disease, N. 2007b. Association between proximity to the attending nephrologist and mortality among patients receiving hemodialysis. *CMAJ Canadian Medical Association Journal.* 177(9), pp.1039-1044.

Tonelli, S.M., Rakel, B.A., Cooper, N.A., Angstom, W.L. and Sluka, K.A. 2011. Women with knee osteoarthritis have more pain and poorer function than men, but similar physical activity prior to total knee replacement. *Biology of sex differences.* 2, pp.12-12.

Towheed, T. and Hotchberg, M. 1996. Health-related quality of life after total hip replacement. *Semin Arthritis Rheumatology.* 26(1).

Tracey, E., Hacker, N.F., Young, J. and Armstrong, B.K. 2014. Effects of Access to and Treatment in Specialist Facilities on Survival From Epithelial Ovarian Cancer in Australian Women A Data Linkage Study. *International Journal of Gynecological Cancer.* 24(7), pp.1232-1240.

Tracey, E., McCaughan, B., Badgery-Parker, T., Young, J. and Armstrong, B. 2015a. Survival of Australian lung cancer patients and the impact of distance from and attendance at a thoracic specialist centre: a data linkage study. *Thorax.* 70(2), pp.152-160.

Tracey, E., McCaughan, B., Badgery-Parker, T., Young, J. and Armstrong, B.K. 2015b. Patients with localized non-small cell lung cancer miss out on curative surgery with distance from specialist care. *Anz Journal of Surgery.* 85(9), pp.658-663.

Trust, T.L.T.H. 2019. *Hospitals of the Future* [Online]. [Accessed 19 March 2019]. Available from: http://www.futurehospitalsleeds.co.uk/

Tudor Hart, J. 1971. THE INVERSE CARE LAW. *The Lancet.* 297(7696), pp.405-412.

UK Data Archive. 2018. *UK Data Archive.* [Online]. [Accessed 17 December 2018]. Available from: http://data-archive.ac.uk/

Uresson, C. and Matteson, E. 2013. Malignancy as a comorbidity in rheumatic diseases. *Rheumatology (Oxford).* 52, pp.5 - 14.

Vallejo-Torres, L., Melnychuk, M., Vindrola-Padros, C., Aitchison, M., Clarke, C.S., Fulop, N.J., Hines, J., Levermore, C., Maddineni, S.B., Perry, C., Pritchard-Jones, K., Ramsay, A.I.G., Shackley, D.C. and Morris, S. 2018. Discrete-choice experiment to analyse preferences for centralizing specialist cancer surgery services. *BJS.* 105(5), pp.587-596.

van Schaardenburg, D., Breedveld, F.C., Otten, H.G. and Lagaay, A.M. 1993. THE RELATION BETWEEN CLASS-SPECIFIC SERUM RHEUMATOID FACTORS AND AGE IN THE GENERAL POPULATION. *Rheumatology.* 32(7), pp.546-549.

Vaughan, M., Felson, D., LaValley, M., Orsmond, G., Niu, J., Lewis, C., Segal, N., Nevitt, M. and Keysor, J. 2017. Perceieved Community Environnental Factors and Risk of Five- Year Participation Restriction Among Older Adults With or at Risk of Knee Osteoarthritis. *Arthritis Care & Research.* 59(7), pp.952 - 958.

Vina, E. and kwoh, C. 2018. Epidemiology of osteoarthritis: literature update. *Current opinion in rheumatology.* 30(2), pp.160-167.

Walters, S.J. and Brazier, J.E. 2005. Comparison of the minimally important difference for two health state utility measures: EQ-5D and SF-6D. *Quality of Life Research.* 14(6), pp.1523-1532.

Wang, F., Mclafferty, S., Escamila, V. and Luo, L. 2008a. Late-stage breast cancer diagnosis and healthcare access in illinois. *Professional Geographer.* 60(1), pp.54-69.

Wang, F., McLafferty, S., Escamilla, V. and Luo, L. 2008b. Late-stage breast cancer diagnosis and health care access in illinois. *Professional Geographer.* 60(1), pp.54-69.

Ware, J., Krosinski, M. and Keller, S. 1996. A 12-Item short-form health survey: Construction of scales and preliminary tests of reliability and validity. *Medical Care* 34(3), pp.220-233.

Ware, J.E. and Sherbourne, C. 1992. The MOS 36-item Short-Form Health survey (SF-36). *Medical Care.* 30, pp.473-483.

Wasif, N., Pockaj, B.A., Gray, R.J. and Etzioni, D.A. 2014. Distance travelled is an unrecognized bias for short and longterm outcomes following complex gastrointestinal cancer surgery: Results from the national cancer database. *Annals of Surgical Oncology.* 1), pS28.

West Midlands. 2006. *West Midlands Local Transport Plan.* [Online]. [Accessed 10 January 2019]. Available from: http://ww.letzgogreen.org/2006/section_55.html

White, J., Zaninotto, P., Walters, K., Kivimäki, M., Demakakos, P., Biddulph, J., Kumari, M., De Oliveira, C., Gallacher, J. and Batty, G.D. 2016. Duration of depressive symptoms and

mortality risk: the English Longitudinal Study of Ageing (ELSA). *The British Journal of Psychiatry.* 208(4), pp.337-342.

WHO. 1946. Preamble to the Constitution of the World Health Organisation as adopted by the International Health Conference. [Online]. [Accessed 10 January 2019]. Available from: https://www.who.int/governance/eb/who_constitution_en.pdf

WHO. 2001. Madrid Statement: Mainstreaming gender equity in health: the need to move forward. [Online]. [Accessed 26 March 2019]. Available from: http://www.euro.who.int/en/health-topics/health-determinants/gender/publications/pre-2009/mainstreaming-gender-equity-in-health-the-need-to-move-forward.-madrid-statement

WHO. 2008. *2008 - 2013 Action plan for global stratedy for the prevention and control of noncommunicable diseases.* [Online]. [Accessed 26 March 2019]. Available from: https://www.who.int/nmh/publications/9789241597418/en/

WHO. 2016. *International Statistical Classification of Diseases and Related Health Problems 10th Revision.* [Online]. [Accessed 05_01_2016]. Available from: http://apps.who.int/classifications/icd10/browse/2016/en

WHO. 2019. *Health equity* [Online]. [Accessed 26 March 2019]. Available from: https://www.who.int/topics/health_equity/en/

Williams , D., Price, A., Beard, S., Hadfield, S., Arden, N.K., Murray, D. and Field, R. 2013. The effects of age on patient-reported outcome measures in total knee replacements. *The bone and Joint Journal.* 95, pp.38 - 44.

Williams, R. 2006. Generalized ordered logit/ partial proportional odds models for ordinal dependent variables. *STATA journal.* 6, pp.58-82.

Wilson, K. and Goldsmith, C. 1999. Does smoking cause rheumatoid arthritis? *The Journal of Rheumatology.* 26(1), pp.1-3.

Woo, Y., Kyrgiou, M., Bryant, A., Everett, B. and Dickinson, H. 2012. *Centralisation of care may prolong survival in women with ovarian cancer and possibly more generally gynecological cancer.* [Online]. [Accessed 10 January 2019]. Available from: http://summaries.cochrane.org/

World Bank. 2019. *World Bank data by Country* [Online]. [Accessed 11 January 2019]. Available from: https://data.worldbank.org/country

Young, A., Dixey, J., Kulinskaya, E., Cox, N., Davies, P., Devlin, J., Emery, P., Gough, A., James, D., Prouse, P., Williams, P. and Winfield, J. 2002. Which patients stop working because of rheumatoid arthritis? Results of five years' follow up in 732 patients from the Early RA Study (ERAS). *Annals of the Rheumatic Diseases.* 61(4), p335.

Zgibor, J., Gieraltowski, L., Tallbot, E., Fabio, A. and Sharma, R. 2011. The association between driving distance and glycemic control in rural areas. *Journal Diabetes Science and Technology.* 5(3), pp.494-500.

Zorzi, D., Rastellini, C., Freeman, D.H., Elias, G., Duchini, A. and Cicalese, L. 2012. Increase in mortality rate of liver transplant candidates residing in specific geographic areas: analysis of UNOS data. *American Journal of Transplantation.* 12(8), pp.2188-2197.

Appendix 1: Systematic Review Search Terms for MEDLINE

Intervention/ Comparator terms	Population accessing Healthcare	Health Outcomes
Proximity adj3 health*.ti,ab	health*adj3 access*.ti,ab	Health status.ab,ti
Proximity adj3 hospital*.ti,ab	health* adj3 care.ti,ab	Health inequal*.ab,ti
Travel*.ab,ti	health* adj3 facilit*.ti,ab	"health related quality of life".ab,ti
Distance*.ab,ti	hospital*.ti,ab	Hrqol.ab,ti
Patient adj3 transport.ti,ab	inpatient*.ab,ti	Mortality.ab,ti
Journey*adj5 (car or bus or transit or transport* or public transport or train).ti,ab	outpatient*.ti.ab	Delay* adj3 diagnosis.ab,ti
Time to hospital*.ab,ti	health* adj3 appoint*.ab,ti	Late* adj3 diagnosis.ab,ti
Transportation of patients/	rural adj3 health*.ab.ti	Miss*adj3 appoint*.ab,ti
Travel/	urban adj3 health*.ab,ti	Health adj3 outcome.ab,ti
	communit* adj3 health*.ti,ab	Quality of life.ab,ti
	primary health*.ab,ti	Self reported health.ab,ti
	family practice.ab,ti	Prognosis.ab,ti
	gen* pract*.ab,ti	Complete adj3 treatment.ab,ti
	health* adj3 screen*.ti,ab	Did not attend.ab,ti
	clinic.ab,ti or clinics.ab,ti	Health status/ or health status disparities/
	GP.ab,ti	*"Quality of life"/ or patient compliance/ or patient refusal/ or diagnosis/ or delayed diagnosis/
	"accident and emergency".ab,ti	Mortality/
	health services accessibility/	Prognosis/

	hospitals/ or hospitals, community/ or hospitals, general/ or hospitals, group practice/ or hospitals, high-volume/ or hospitals, low-volume/ or hospitals, private/ or hospitals, public/ or hospitals, rural/ or hospitals, satellite/ or hospitals, special/ or hospitals, teaching/ or hospitals, urban/ or mobile health units/ or secondary care centers/ or tertiary care centers/Appointments and schedules/	Treatment adj3 retention.ab,ti
	Mass screening/	Treatment adj3 follow adj3 up.ab,ti
	Urban health/	Patient complian*.ab,ti
	Rural health/	
	Health services/ or primary healthcare/ or general practice/ or tertiary healthcare/	
	Emergency service, hospital/	

Restrictions	NOT exercise test/ or exercise test.ab,ti
	English Language

Appendix 2: Health outcome measures used to assess health/ quality of life outcomes following THR and TKR

Outcome measure	Abrev.	Generic	Joint Specific		Type of measure		Description	Source
			Hip	Knee	Quality of life	Objective tool		
Harris Hip Score	HSS		✓			✓	The HHS is a clinician assessed outcome measure focused on the domains of – pain, function, absence of deformity and range of motion. It is scored out of 100 (the best outcome is 100).	Nilsdotter and Bremander (2011)
Knee Society Score	KSS			✓	✓	✓	This measure was designed as an objective tool, but has been adapted over time to include both clinician and patient input. It involves an initial assessment of demographic details, including an expanded Charnley functional classification. The objective knee score, completed by the surgeon, includes a VAS score of pain, walking on level ground and on stairs or inclines, as well as an assessment of alignment, ligament stability, and ROM, along with deductions for flexion contracture or extensor lag. Patients record their satisfaction, functional activities, and expectations.	Scuderi et al. (2012)
Hip outcome Score	HOS		✓		✓		The HOS was developed to apply to younger patients (< 60) and the reflect differences in what they might want to achieve. It is based on two scales focusing on abilities to undertake - *Activities of daily life* and secondly *sporting activities.* The results from these scales are combined to give a scale between 0 and 104 (higher score means greater level of function.	Martin and Philippon (2008)
Western Ontario and McMaster Universities Arthritis Index	WOMAC		✓	✓	✓		The WOMAC is a 24 item questionnaire in the three domains of: pain, joint stiffness and physical functioning. Score between 0 and 96. Higher scores represent a worse health outcome. Developed to measure the health status of patients following hip or knee operations.	Bellamy et al. (1988)
Knee disability and Osteoarthritis Outcome Score	KOOS			✓	✓		Developed from the WOMAC. It includes 5 subscales: Pain (10 items), Symptoms (5 items), Activity of Daily Living (17 items), Sport and Recreation Function (4 items) and Hip Related Quality of Life (4 items). A total score is calculated by using a formula to produce a score that ranges from 0-100 with higher scores representing better function.	ROOS et al. (1998)
Hip disability and Osteoarthritis Outcome Score	HOOS		✓		✓		Developed from the WOMAC and adapted from the KOOS. Same description as KOOS but applied to the hip.	ROOS et al. (1998)
Oxford Hip Score	OHS		✓		✓		This patient completed questionnaire consists of 12 questions designed to assess function and pain over the previous 4 weeks for patients undergoing hip replacement surgery. The results are summed to give a score between 0 and 48 (higher is better).	Dawson et al. (1996)
Oxford Knee Score	OKS			✓	✓		This is the knee equivalent of the OHS. Discussed in Chapter 3.	Dawson et al. (1998)

EQ-5D-3L		✓			✓		This patient completed questionnaire measures health across five domains: mobility, self-care, usual activities, pain/discomfort and anxiety / depression. Discussed in greater detail in Chapter 3.	The EuroQol Group (1990)
EQ-5D-3L Visual Analogue Scale	EQ-5D VAS	✓			✓		This VAS asks patients how good or bad their health on a scale of 0 – 100. It was designed to be used alongside the EQ-5D-3L. Discussed in Chapter 3.	The EuroQol Group (1990)
36 Item Short Form Survey	SF36	✓			✓		This patient completed questionnaire measures health across eight areas: role limitations due to physical health, role limitations due to emotional problems, energy/fatigue, emotional wellbeing, social functioning, pain and general health. Each area is scored between 0 and 100.	Ware and Sherbourne (1992)
12 Item short form survey	SF12	✓			✓		This patient completed questionnaire was developed as a shorter sub set of the SF36.	Ware et al. (1996)
General Health		✓			✓		This general questionnaire asks the question - *In general, would you say that your health is excellent, very good, good, fair, or poor?.* As well as being used on its own it forms one question in both the SF12 and SF36.	
Lower Extremity Functional Scale	LEFS		✓	✓	✓		This patient completed questionnaire asks twenty questions about level of difficulties with general activities on a five point scale from *extreme/ unable to do* to *no difficulties*. The scores are summed to give a maximum of 80. The lower the score the lower the functional ability.	Binkley (1999)
Timed Up and Go Test	TUG	✓				✓	Measures the time to get up out of a chair and walk 3 metres.	Podsiadlo and Richardson (1991)
Stair Climbing Test	SCT	✓				✓	Measures the time to ascend and descend a flight of stairs.	Hughes et al. (1998)
6 – minute walk test	6 mWT	✓				✓	Measures how far patients can walk in 6 minutes.	(Ko et al., 2013)
Single Limb Stance Time	SLST	✓				✓	Measures how long a patient can stand one legged with their eyes open.	Potvin et al. (1980)
Range of Motion	ROM		✓	✓		✓	Measures the range of movement around a joint.	Roach and Miles (1991)
Complications		✓				✓	There are a number of potential complications from having a TKR or THR. These include: blood clots, differing length of legs, joint dislocations, fractures and infections.	Healy et al. (2016)
Infection Rate		✓				✓	Joint Infection rate following the operation.	Peersman et al. (2001)
Length of Stay in Hospital		✓				✓	Number of days in hospital following the operation.	Burn et al. (2018)
Blood loss during surgery		✓				✓	Quantity of blood loss during the operation.	Browne et al. (2013)
Mortality		✓				✓	Death during the operation or a certain time points following the operation.	Hunt et al. (2017)

Revision Rate			✓	✓		✓	This is the failure rate for hip or knee replacements operations.	Lenguerrand et al. (2017)
Charnley hip score			✓		✓	✓	This score has input from the clinician and patient. The Charnley hip score assesses pain, hip movements, and walking each on a scale of 0-6, but does not combine to obtain a total score.	Charnley (1972)
Mayo Clinical hip score			✓		✓		The Mayo hip questionnaire completed by patients assesses the domains of pain, function and mobility. It generates a total score clinical score ranging 0-80 (Excellent result is 72-80 points, good is 64-71 points, fair is 56-63 points, and poor is less than 55 points)	Singh et al. (2016)
Nottingham Health Profile	NHP	✓			✓		The NHP was developed to be used in epidemiological studies of health and disease. It consists of two parts. Part I contains 38 yes/no items in 6 dimensions: pain, physical mobility, emotional reactions, energy, social isolation and sleep. Part II contains 7 general yes/no questions concerning daily living problems.	Hunt and McEwan (1980)